An Introduction to Corporate Modeling

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To Gisela, Jan, and Philipp

Foreword

Dr. Friedrich Rosenkranz has assembled in this impressive volume what I would consider to be the state-of-the-art of corporate modeling. It represents the definitive work in a dynamic, rapidly changing field.

Over ten years in the making, An Introduction to Corporate Modeling outlines theory, methodology, and practice of corporate planning models based on extensive experience and empirical testing at CIBA-GEIGY, the Swiss chemical and pharmaceutical giant.

The book contains a unique conceptual framework for corporate modeling which makes use of graph signal flow diagrams. The methodologies for financial, marketing, production,and manpower planning models are developed with careful precision. Considerable attention is also given to the relationship between corporate simulation models and the planning process of corporations.

Dr. Rosenkranz and his colleagues at CIBA-GEIGY have also developed a special purpose planning and modeling software system known as COMOS. Most of the corporate planning models included in the book have been implemented by CIBA-GEIGY using COMOS.

Each chapter contains the most extensive bibliography on corporate modeling that is available anywhere today.

Both academic and real world planning managers, and analysts should find this book to be an extremely powerful and useful reference book on corporate modeling. It contains a wealth of valuable information for practitioners and theoreticians alike.

The real power underlying this book is that literally every model and every technique described in the book has been used and tested extensively during the past ten years in one or more of the operating divisions of CIBA-GEIGY. Not only should Dr. Rosenkranz be congratulated for this monumental contribution to the literature on corporate modeling, but the management of CIBA-GEIGY should also be commended for providing an environment

which was highly conducive to the implementation of innovative management tools.

This book should be required reading for anyone who is seriously interested in planning, modeling, and management science.

Thomas H. Naylor
Duke University and SSI
January 1, 1979

Preface

This book deals with the development of a conceptual framework for the construction, verification and implementation of corporate simulation and planning models.

Within this context, a corporate model is assumed to be an abstraction of the development and operation of a firm. The abstraction is achieved by the formulation of equations and logical relationships to describe the firm in the areas of finance, production and marketing. The model equations and relationships are often expressed in the form of computer code.

The work described in this book has, to a large extent, been carried out within one company - the CIBA-GEIGY Corporation in Basle, Switzerland. In such an environment, it was necessary to develop practical methods and intelligible results. Although the book contains discussion and reference to theoretical corporate modeling work, it is primarily applications oriented.

Corporate modeling activities within CIBA-GEIGY started in 1970. In contrast to what is read and heard of global models of other firms, no single "CIBA-GEIGY corporate model" exists today. Modeling efforts have been undertaken with varying success for a number of different applications. Some models having one or more segments from the areas of finance, marketing and production, exhibit a tendency to integrate these functions. That is, they possess a "hard core" corporate financial or marketing model with the other segments expressed in less detail. In short, within CIBA-GEIGY, there exists a variety of corporate modeling applications which are characteristic of modeling efforts made by many other companies. The book tries to supply a common methodology for such heterogeneous applications and gives suggestions for model integration.

In chapter 1, the nature of a corporate model and its potential

applications within a company's planning, organizational and decision process is outlined. In chapter 2, a tour d'horizon of methodological and application problems is given and a conceptual framework of corporate modeling is developed. Chapters 3 through 8 are devoted to corporate modeling methodology and chapter 9 describes some practical examples and case studies.

A great number of people have either directly or indirectly helped in the preparation of this book. Especially, the author wants to express his thanks for the continuous and generous support of the CIBA-GEIGY Control and Management Services, notably W. Heim, Dr. A Krauer, and F. Zappa. The author has been in the favorable position to draw on the implicit wisdom and distributed knowledge of a large corporation.

My colleagues, Dr. David Hare and Dr. Sergio Pellegrini gave a great number of helpful and inspiring comments. Encouragement from other people working in the field, notably Professors Wilhelm Hill, Thomas H. Naylor and Norbert Szyperski is greatly acknowledged. Prof. Peter Grinyer, Prof. Thomas H. Naylor and their respective publishers have kindly given permission to reporduce some of their survey results in the first three chapters of this book.

Discussions with H. Kränzlin and Dr. S. Pellegrini strongly influenced the development of the CIBA-GEIGY Corporate Modeling System and Language (COMOS). A great deal fo the encessary programming has been carried out by E. Boissaye, R. Bürgisser, R. Golbeau and H. Kränzlin. The examples, case studies and models described have been developed with the support of D. Arendt, E. Boissaye, Dr. P. Kugler (Marketing), Dr. S. Pellegrini (Finance), E. Boissaye, Dr. S. Pellegrini (Production), Ch. F. Hobday, G.R. Reah (Decision Calculus), Dr. R. Lindenmayer (Industrial Dynamics) and P. Pfister (Box-Jenkins Analysis), Prof. Thomas H. Naylor and members of Social Systems Inc. (SSI) have assisted in the editing of this book. However, any errors remaining in the following chapters are the author's sole responsibility.

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Basle, May 1978

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An Introduction to Corporate Modeling

Introduction

CORPORATE MODELS DEFINED

The following chapters will deal with the construction of corporate simulation and planning models (CSPMs). During the past ten years, a great number of reports, articles and surveys have appeared on this subject describing a variety of modeling applications. The current activities and ongoing software developments of computer manufacturers and consulting companies indicate a large and still growing demand for planning models. Considering this empirical evidence one may conclude that CSPMs are indeed used in practice.

This fact is rather surprising if one considers, on one hand, the skepticism many managers and planners still have with respect to the application of quantitative methods and, on the other hand, the unstable environment and the profit squeeze which has made these same people more cost conscious. In this situation, one may safely infer that corporate models are helpful for planning and decision support purposes. However, this conclusion is over-simplified by the absence of a common definition of a corporate simulation and planning model.

A TENTATIVE DEFINITION

The models which are described in the literature are quite heterogeneous and a structuring of the hypotheses and objectives underlying the construction of CSPMs seems to be largely missing. It is this very fact which caused Gershefski to remark "... no generally accepted definition of a corporate model exists [50, p.43]." Boulden, another pioneer

in the field of computer-based planning and modeling, notes for computer-assisted planning systems in general "... an incomfortably large body of material remains that is pragmatic and supportable only in that it seems to work [21, p. XIV]." With CSPMs one seems to deal with the very rare case in the management sciences that models are constructed and implemented with some success before they are structured by either an existing or new theory.

Naylor describes corporate models as "... an attempt to describe the interrelationships among a corporation's financial, marketing and production activities in terms of a set of mathematical and logical relationships which are programmed into the computer [81]." These relationships "... represent, in detail, the physical operations of the company, the accounting and financial practices followed and the response to investment in key areas (Gershefski [50, p.44])."

These general definitions are compatible with the framework used by earlier theories of the firm, such as the classical theory of the firm, as well as more recently developed organizational, behavioral or budgeting oriented theories and concepts (e.g., Simon [102], Cyert and March [30], Mattesich [78]). However, due to the extreme implementation and data oriented nature of most models known today, CSPMs do not rely on the body of a single theory. They are rather based on elements of different theories or use assumptions purely because of pragmatic reasons (viz. Naylor [83]).

As a working definition, a corporate simulation and planning model will be understood to be a description and explanation of a complete firm and its development or activity in time and at different locations. This description is achieved by the specification, estimation and solution of equations to reproduce the behavior of a firm in the functional areas of finance, production and marketing as well as different organizational units. Such a model is based on the qualitative and quantitative, subjective as well as objective information available in the firm. Data, relations and methods used with a corporate model are stored or programmed for a computer. Although corporate models to a large extent serve descriptive and explanatory purposes, the main objective behind their construction and use is normative: the models should generally indicate key areas of the firm's activities which can be controlled by its management in such a way that further activities in the future can be guaranteed or improved (Rosenkranz, Pellegrini [96]).

This definition contains many terms and concepts which deserve further explanation. Several survey results show how our definition may be interpreted with respect to existing models. A short description of environmental problems and technological developments provides further reasons for the use of CSPMs and draws the line between corporate and environmental modeling. The following section contains a brief outline of the historical development of CSPMs followed by a discussion of limitations of our definition. Finally, the questions of goals and objectives of the firm is treated.

SOME SURVEY RESULTS

A great amount of information is available today which allows conclusions with respect to the nature and use of corporate models. More than a hundred models are described either in professional journals, books [21, 52] or proceedings of conferences which have taken place at the University of Washington, 1970 [99]; Torremolinos, 1972 [42]; Cologne University, 1972 [53]; Bad Homburg, 1976 [89]; and San Francisco, 1977 [86].

Some partial evaluation of this secondary information has been attempted by Dickson, et al [36] and Grinyer and Batt [51]. These authors have also tried to supplement their evaluations by direct interviews and contacts with model builders and users. Boulden supplied a survey of fifty-five modeling applications which is based on his consulting experiences [20].

Rosenkranz and Pellegrini [96] and Rosenkranz [97] so far seem to give the most extensive descriptions of the corporate modeling activities within one single company.

Primary information on corporate models is mainly available from three sources. In 1969, Gershefski carried out a questionnaire survey of 1900 American companies [49]. He achieved a response rate of 17 percent and identified 63 companies who claimed to be either using or developing a corporate model. In 1973, Grinyer and Wooller [52] concluded from a questionnaire survey (which was checked by some telephone interviews) that nine percent of the largest UK companies, 'The Times 1000,' had or were developing corporate models. In their evaluation, they structured the applications in 65 companies. In 1974, Naylor and Schauland carried

out a non-random survey by sending questionnaires to some 1880 American and European companies [85]. They had a response rate of 19 percent and identified some 240 companies which either used or were in the process of developing a corporate model.

The available information on corporate models should be interpreted. Articles, interviews and surveys deal mainly with models which have successfully been implemented. Although Naylor supplies the names of a number of companies who have failed in the construction of a corporate model [84], a more than qualitative discussion of failures or the problem of model life cycles is largely missing. Articles in professional journals tend to create a more formal, structured and mathematical picture than might be the case in practice [51, p.67]. Due to the limited time respondents of a questionnaire are willing to spend, questions tend to be short and not very specific, answers are of the dichotomous type and reports on tests of the questionnaires are largely missing. Terms like 'model' or 'cash flow analysis' are understood quite differently. Grinyer and Wooller define corporate models as "... sets of related expressions that represent the key operations of the company" and remark "...in their most common form, they comprise little more than accounting statements linked in a straightforward way [52, p.1]." Others would call this an accounting model only, since marketing and production activities of a company are only described in monetary values, not quantities like volume or capacity. In total, the answers to the questionnaires are likely to incorporate many ambiguities and misinterpretations.

Although many objections may result with respect to the cited evaluations, one should note that they are not contradictory and should at least allow tentative conclusions. Some results which are interesting with respect to the definition of corporate models given above are briefly discussed in the following section.

USE AND AREAS OF APPLICATIONS

Figures 1.1 and 1.2 indicate the major uses of corporate models as obtained by Grinyer/Wooller and Naylor/Schauland.

Figure 1.1. Major uses of models [52]

Application		Percentage of companies (%)
(A)	Financial	
	Financial planning (up to 1 year)	38
	Financial planning (1 to 5 years)	78
	Financial planning (over 5 years)	45
	Cash flow analysis	75
	Financing	14
(B)	Non-financial planning	
	Aid marketing decisions	65
	Market share forecasting	8
	Aid production decisions	60
	Aid distribution decisions	38
	Aid purchasing decisions	11
	Manpower planning	12
(C)	Evaluation of special projects	
	Project evaluation	45
	New venture evaluation	14
	Acquisition studies	12
	Computer evaluation (rent or buy)	5

Both results are consistent with the definition in the sense that models deal with the functional areas of finance, marketing and production. The sequence of these areas also indicates the frequency with which they are described by a model. All the available literature indicates that the financial area of a company is most frequently described. The extent to which companies have succeeded in an integrated description of all three areas is rather uncertain. Figure 1.3 shows the output produced by the models according to the Grinyer/Wooller survey. From it, one may draw conclusions with respect to the required input information. One may also observe that modeling activities deal with location aspects and cover several organizational levels. Figure 1.3 does not reveal the extent of organizational and functional model integration. The literature

and comments in the surveys suggest that this is still more the exception rather than the rule.

Figure 1.2. Applications of corporate models [85]

Application	Percentage of companies (%)
Cash flow analysis	65
Financial forecasting	65
Balance sheet projections	64
Financial analysis	60
Pro forma financial reports	55
Profit planning	53
Long-term forecasts	50
Budgeting	47
Sales forecasts	41
Investment analysis	35
Marketing planning	33
Short-term forecasts	33
New venture analysis	30
Risk analysis	27
Cost projections	27
Merger-acquisition analysis	26
Cash management	24
Price projections	23
Financial information system	22
Industry forecasts	20
Market share analysis	17
Supply forecasts	13

However, Figure 1.4, which is taken from the Grinyer/Wooller survey, shows that a considerable percentage of models, even at the corporate level, describe financial and/or physical quantities as would be required for model integration especially for applications in the marketing and production areas.

Figure 1.3. Output reports produced by models: percentage of companies with each report [52]

Report	Total company %	Subsidiaries %	Divisions %	Operating units %
Profit and loss	98	43	40	22
Balance sheet	79	37	25	12
Cash flow	77	37	28	15
Financial ratio analysis	68	31	23	18
Source and use of funds statement	55	28	20	11
Marketing operation	34	25	31	23
Project evaluation	34	25	12	15
Production	34	22	28	22
Distribution	29	17	20	17
Purchasing	11	8	8	6
Manpower	9	6	9	6
Financing	8	2	2	2
New Venture	3	2	3	2

Figure 1.4. Use of financial and physical quantities [52]

	Financial flows represented (% of companies)	Physical flows represented (% of companies)
Corporate level	100	57
Subsidiary level	82	51
Divisional level	70	45
Operating unit level	43	30

TIME FRAME

By definition, a corporate model describes the development of a firm's variables as a function of time. Figure 1.5 shows the frequency with which different time frames are used for this purpose.

Although some propositions have been made for the construction of static corporate models (viz. Virts and Garrett [113], Hansmann [58]), they seem to be an exception from the rule. In most cases, a yearly time frame is used. A mean planning or future time horizon of five to eight years indicates that most models seem to be used for middle term financial planning purposes. However, a considerable portion is used with a monthly time frame. This indicates a support of operational plans, probably to a larger extent in the marketing and production areas.

Figure 1.5. Time frame used with corporate models

	% of companies			
	Gershefski [49]	Grinyer/ Wooller [52]		Naylor/ Schauland [85]
Year	(72)	51	(75)	45
Quarter	(13)	3	(13)	5
Month	(15)	11	(36)	14
Combinations	no answer	30	(n.a.)	33

MODEL STRUCTURE AND EVALUATION

It is extremely difficult to draw general conclusions about the structure of corporate models from the evaluation of a questionnaire survey. Only Naylor and Schauland [85] have tried this and their results need to be interpreted with respect to the known structure of the published models.

There is no standard size of a CSPM with respect to the number of equations it contains. A model may consist of, say, twenty equations involving heavily aggregated variables. Such an approach is typically taken with models similar to classical models of the firm. The model by

Burill and Quinto [24], developed by IBM for educational purposes, is such an example (viz. also Virts and Garrett [113]). On the other hand, other models use up to several thousand equations (Rosenkranz, Pellegrini [86]). These may be of a very simple and straightforward nature and reducible to approximately a hundred equations if vector and matrix notation is used.

A more meaningful relation to characterize the structure of a CSPM seems to be the relation of the number of purely definitional equations in a model to the number of equations which incorporate, for example, economic behavior.

A definitional equation would be

PROFIT = SALES - COSTS ,

whereas, an equation which describes sales volumes for a product as a function of price would be of the behavioral type, since it may be based on hypotheses about the behavior of a sales market.

All references agree that the predominant number (80 - 95%) of equations contained in a corporate models are of the definitional, mostly accounting type. However, it should be noted in this context that a reduction of this number is always possible by substitutions and it is largely determined by the type of model output a user wants to obtain (viz. Fig. 1.3.).

Identities do not need to be estimated. The solution of a model largely consisting of identities rarely requires the use of a solution method other than right hand side variable substitution (i.e., solution of a system of independent or recursive equations). It is, therefore, not surprising that more advanced solution methods, as would be needed for the solution of simultaneous equations, are not as frequently used.

Behavioral equations in a model have to be estimated and somehow verified and validated with respect to what happens in reality. In most cases, this seems to be done subjectively. A model user, for example, will assume the functional form and the parameters in a price-demand equation and be content with it, if it reproduces reality in a satisfactory manner. The user would not use any formal testing of assumptions. In contrast to this observation, there is a large number of models remaining for which equations are estimated statistically, mostly by linear regression techniques. Also econometric specification testing and more formal validation methods are in use. From both the Gershefski and Naylor/Schauland surveys, one can conclude that between ten to thirty

percent of the companies in the sample used some statistical and some estimation techniques.

There can be no doubt that, in general, there is a lot of chance and randomness involved in real world relations, especially between a company and its environment. Random variables in the model equations may represent such effects. A statistical estimation of behavioral equations implicitly takes such effects into consideration. However, only comparatively few companies consider random variables or employ risk analysis techniques in the solution of their models. According to Gershefski and Naylor/Schauland, only five to ten percent use stochastic variables. Grinyer/Wooller and Grinyer/Batt obtain higher percentages. It must be concluded that the overwhelming number of models developed thus far are of a deterministic nature.

INFORMATION USED

To our knowledge, there is as yet no systematic evaluation available which shows what type of information corporate models are based on. However, it seems that information available from a company's internal information system is utilized in practically all modeling applications. Such information may come from accounting and financial systems, sales reports, bills of materials and may - as especially Gershefski [49] mentions - be generated by a company's formal planning procedure. The Naylor/Schauland survey indicates that nearly 60 percent of the firms using corporate models purchase external information from national econometric forecasting services [85]. It is not exactly clear how this information is used in the models. A survey by Keegan indicates that a computer based evaluation of external information is still more the exception than the rule [70]. However, this may have changed during the past few years. A number of examples are known in which external information and forecasts were directly fed into corporate models [32,56].

Subjective and qualitative information is mainly used if hypotheses for a model run are specified. It should be noted that a clear distinction between the types of information used is not always possible, since accounting information as well as macroeconomic forecasts may incorporate value judgements and a considerable amount of intuition.

WHY CORPORATE MODELS

Most corporate models were constructed by business to support their planning process. The literature contains various examples of corporate models which were intended as educational tools or management training devices, as demonstration models designed to show that a certain theory or concept of the firm or a certain solution technique could be made operational in a formalized fashion [15, 18, 24, 30, 43, 45, 66, 77, 79]. However, these examples are relatively few in number. The impact they have had on the development of planning models is not easy to trace and will be discussed separately.

The main thrust for the development of CSPMs came from firms who were looking for planning tools in a qualitatively and quantitatively new planning situation. This situation has been created by the status of the planning technology, the development of computer hard-and software and last, but not least, by abrupt qualitative and quantitative changes in the environment of the firm.

PLANNING TECHNOLOGY

Some ten to twenty years ago, especially larger firms began introducing formal planning procedures which described with different content, time horizon and level of aggregation alternative developments and policies for their future (viz. Gershefski [49, p.B-308]). Various types of planning (e.g., political, strategic, tactical, operational) were distinguished and alternative procedures have been developed in the meantime (viz. Anthony [7], Steiner [105], Szyperski, et al [107], Ansoff, et al [6]). Such procedures describe what type of planning information must be supplied at what time and by whom and how information is aggregated, integrated and reconciled to support planning.

All planning procedures generate both information which is verbally expressed or numerically represented. Especially at the early stages of development, a great amount of numeric information was thus collected and centrally processed. Compared to informal planning, decisions were now put on a more quantitative, perhaps consistent, and objective basis.

However, there were several disadvantages connected with this procedure. Planners were initially absorbed with number crunching and tended to neglect the interpretation of results and the type of planning which could not be described numerically. Plans were conceived as the numerical extrapolation of the present status of a firm. Alternatives were rarely explored and the adaption to a new planning situation was difficult to achieve.

Besides developing other planning procedures, companies started looking for technical planning aids to get relief from clerical work as well as ways to exploit and experiment with planning information.

COMPUTER HARD- AND SOFTWARE

At this stage of planning technology, computer based corporate models would probably have found a widespread application regardless of the environmental disturbances described in the next section. In fact, the surveys by Gershefski [49] and Grinyer and Wooller [52] support this statement. The state of computer hardware and software development allowed the storage and fast evaluation of large quantities of planning information. Telecommunication and terminals made the access to a planning database and planning models for a variety of planners at different geographic locations possible. Special purpose planning software was developed which could be used to program a fast and flexible access to a planning database. Planning languages were used to code alternative planning relationships in the form of planning models. Computer-assisted planning as a whole created the potential for the reduction of routine and clerical planning work. At the same time, it opened the possibility to plan and test alternatives using formalized planning relationships in a laboratory-like environment.

THE ENVIRONMENT

The survey by Grinyer and Wooller [52, p.7] (viz. also Gershefski [49], Naylor and Schauland [85]) indicates that most of the models known today have been built since 1970. About that time, the rather smooth post-war economic development was interrupted by turbulences which posed

many new problems to the planners within the firms. As Ackoff has put it,

> "the growing rate of political, social, economical and technological change has apparently made executives more concerned with the future. Such change has certainly made it easier to do what is wrong (errors of commission) and to fail to do what is right (errors of ommission). To avoid these types of errors that are brought about in an organization's environment, one must grapple with the great and dynamic complexity of that environment and the organization itself [3, p. 21]."

Ansoff speaks of a turbulent environment for the present, an environment characterized by surprises and constraints for the future [6, p.3].

The traditional information systems of companies, such as sales report, bills of materials, reporting oriented accounting systems, and non-computerized short-range and middle-term plans very often, under these circumstances, had difficulties supplying timely and relevant information to the planners. Computer-based planning systems and corporate models are intended to help avoid these shortcomings and resulting planning errors by describing and quantifying the effects changes in a firm's external and internal environment (viz. Boulding [22]) have on its operations. In this context, it is useful to briefly characterize some important environmental changes which contributed to the increased use of corporate models.

WORLD DEVELOPMENT

A nearly exponential growth of the world population, the consumption of energy and certain raw materials over the last hundred years has caused a number of researchers to forecast a stagnating or even contracting world economy mainly for the twenty-first century (Forrester [44], Meadows, et al [80], Gabor and Colombo [46]).

Many researchers, politicians and a large portion of the public believe that the available land and raw material resources can not sustain a continuous exponential growth with increasing industrialization and environmental pollution. A number of global world models were constructed to investigate the interrelationships of important world variables (viz. [29, 27] for a comparison). As an example for one of the earlier models in Figure 1.6, boxes are used to represent important world variables and arrows to show causal links between them (Meadows, et al [80]).

Figure 1.6. Causal structure of world models (viz, Cole, et al [29,p.26])

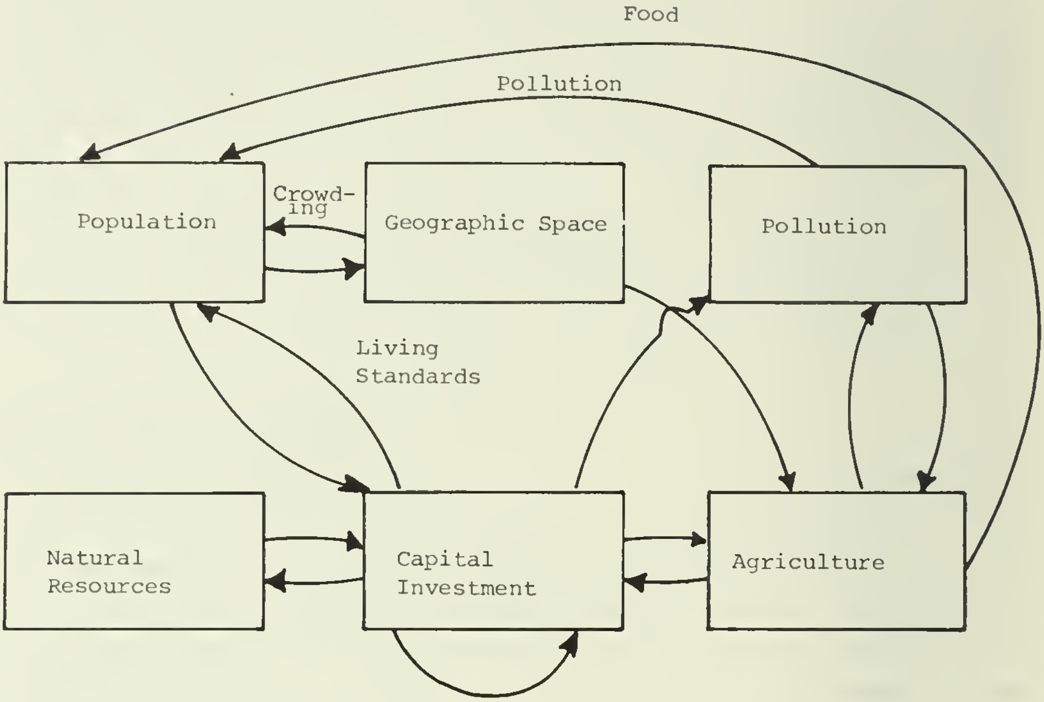
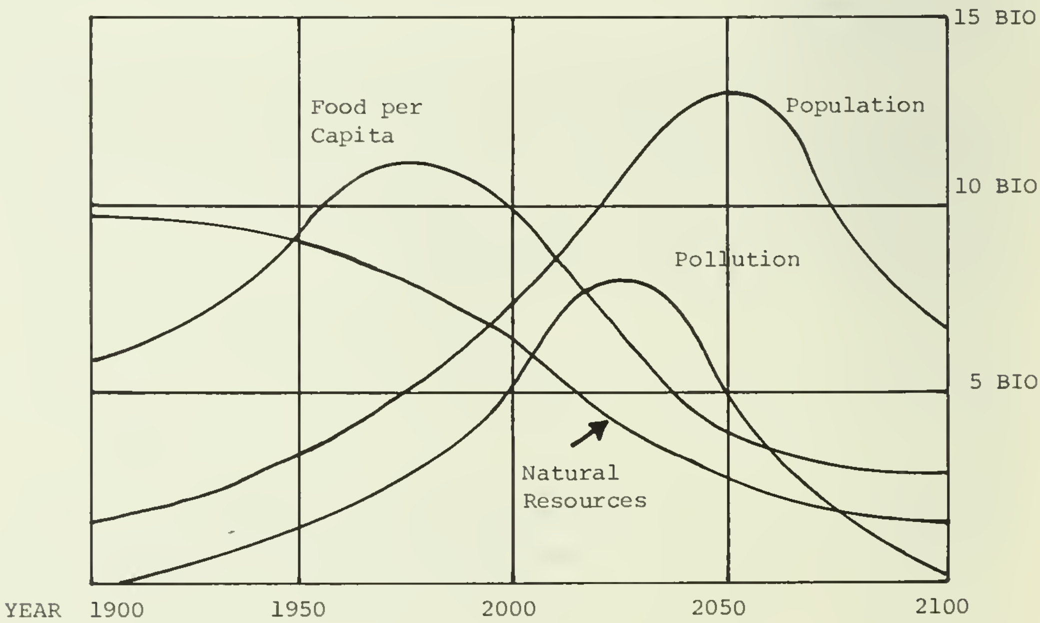


Figure 1.7. Extrapolations from past trends with Meadows World III-Model



According to such a structure, combined with the assumption of limited technological progress and possibilities for product substitution in industry and agriculture, a turning point in economic development should occur. Figure 1.7 shows a result following from the extrapolation of past trends with Meadows' World III-model [28, 80]. The 21st century is characterized by a deterioration of living conditions.

The concept of a finite world used in the original world models has created a lot of economic, political and methogological criticism (viz. e.g. [29, 103, 88, 98]). Further, more partial or detailed modeling activities have resulted in different and conditional forecasts [27]. But such forecasts and the observation of rapidly changing raw material prices and political unrest have sensitized corporate long-range planners. Limits to world growth and problems of interdependent economic developments in the world have become a recognized topic. The construction of early warning systems which could indicate threats and opportunities due to the limited availability or price increases of raw materials, new substitution possibilities and changes in demand or even the effects of changes in the economic and political power constellations are discussed both in practice and the literature (viz. e.g., Ansoff [6]).

Using a computer-based corporate model, a planner may simulate alternative developments of a company's environment. He may test the effects which these developments have on, for example, his company's production process or on its assets in a developing country. Finally, he may simulate the consequences of managerial countermeasures, such as new investments or divestments. Although such "What if?" experiments are not likely to show him a solution to the basic world problems, they may give him a feeling of the risk involved and indicate key factors on which he should concentrate.

INDUSTRIES AND NATIONAL ECONOMIES

The economic development, notably of the last three decades, has led to ever increasing complexity and the interdependence of industries and national economies. European countries and Japan, who largely depend on imports of raw materials and exports of finished goods, and, to a lesser degree, the United States are even in the short-run strongly affected by

economic disturbances in other parts of the world. By influencing complete industries and national economies, disturbances reach individual companies which belong to certain industries or operate in specific countries.

Dynamic inflation rates, the supply of money and trade balance deficits or surplusses, among other factors, influence floating currency exchange rates. A company which operates in several countries faces the problem of valueing its sales, costs and assets. Its financing, hedging or investment policies are likely to be influenced by changing exchange rates. The development and competition of supplying and buying industries in different countries influences prices and the quantities a company may sell to different markets. Varying interest rates in different parts of the world lead to different investment and financing decisions.

As in other areas, planners and managers, notably of multinational companies, urgently need timely and relevant macroeconomic information in order to be able to judge the influence certain macroeconomic developments have on their company.

Quantitative economics, especially econometrics, has made considerable progress during the last three decades. This together with the developments of computer systems allowed the construction of large econometric models of national economies and industries (viz. Naylor [83]), as well as computer-based input-output models which show the interdependence of different industries in an economy. Efforts to link different national econometric models are under way and may result in operational econometric world models [10, 114]. However, there are still a large number of statistical and organizational problems to overcome. At the present time, a large number of econometric models are available for practically all of the major industrialized countries. Many of these models were developed in an academic environment A notable and not representative exception is the IBM Corporation, which constructs macroeconomic models for its own planning purposes, but makes them available to third parties as well (viz. Karchere [89]).

The great demand for macroeconomic information and forecasts has motivated private firms to collect and prepare macroeconomic data and models on a world-wide basis. Such data are locally collected, but centrally stored on online timesharing computers which may be accessed from practically any point in the world via terminal and telephone

transmission. Companies like Data Resources, Chase Econometrics or Economic Models sell data, models and macroeconomic forecasts.

Technically, it is not a great problem to link such information to a company's corporate model. Management may use this method to assess the impact different macroeconomic scenarios and forecasts have on the variables and the status of the company.

NON-ECONOMIC FACTORS

Many disturbances encountered by planners do not arise from disturbances in a company's economic environment, but originate within its organizational, judicial, or socio-political environment. Although these disturbances are of a non-economic and mostly qualitative nature, they have quantitative consequences (viz. Ackoff [5], Ansoff, et al [6]).

Population growth and industrialization have changed or even destroyed old socio-political orders. This has led to political instabilities and social unrest in some parts of the world, and it is unlikely that this transition phase will be completed before the turn of the century.

Notably, companies which either buy from or deliver to such countries are affected by these instabilities. Demand forecasts are difficult to establish. Raw material price or quantity cartels on the supply side may quickly appear and disappear again. Increasing legislation favoring local production is counterbalanced by restrictions on the transfer of profits or the risk of nationalization.

When assessing the development of labor costs and freedom of managerial decision in different countries, planners must be aware of several important changes: for many employees, especially in the western industrialized countries, work no longer plays the sole role of supplying the means to live. This is often taken for granted. Work is also increasingly viewed as a means for self-fulfillment and justification. If these developments are not considered in the design of an organization, the neglect may lead to what is known as "blue collar blues" or strikes and absenteeism. It is very likely that the developments towards "codetermination" and other types of participative structures will continue in the future. Government interventions will probably increase in such areas as antitrust legislation, pollution and safety control and decision making may

develop into "pushing of constraints" (viz. Haselhoff [59, p. 25]).

These developments and disturbances have in common the fact that they are extremely difficult to forecast although they are bound to have strong economic consequences. Under these circumstances, a corporate model may be viewed as a tool for testing the sensitivity and robustness of a company with respect to such changes. Environmental changes are formulated as data input to the model and the model is used as a device to show the impact on the company's output variables.

HISTORICAL BACKGROUND AND SOURCES

Apart from its technical realization and use, the definition of a CSPM given previously is compatible with earlier definitions used with theories of the firm. One may thus say that the object of research is the same and that corporate models may either be representations of hypothetical or real world firms. In both cases, one deals with abstract pictures of microeconomic entities which are characterized by their ability to obtain production factors, e.g., labor, raw and intermediate products, machines and other technical equipment, financial as well as planning, organizational and informational means. They combine and transform these into finished products or services and make them available to their environment (viz. Gutenberg [54, pp. 1-10]). Figure 1.8 visualizes these relations with the classical partition into marketing, production and financial activities.

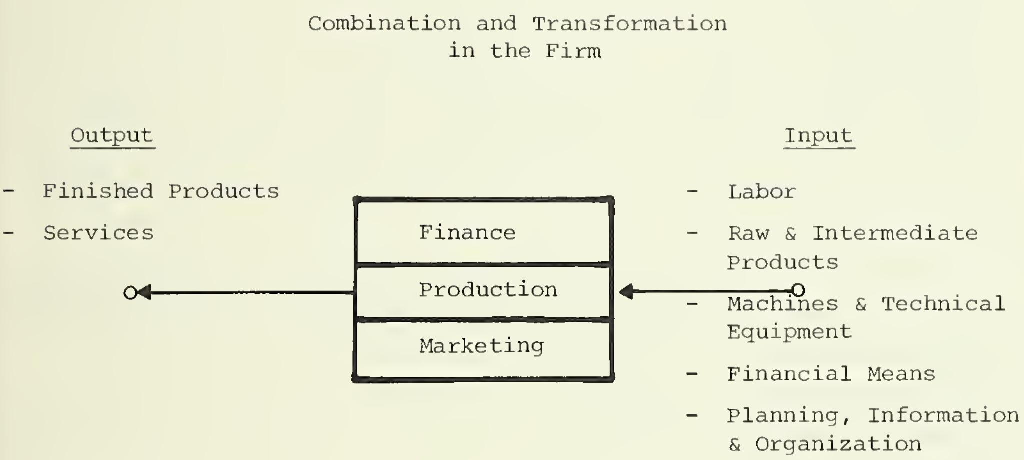
It is possible to imagine and observe a variety of environmental conditions as well as transformation processes that can characterize an individual firm. Depending equally on the social, economic and judicial conditions a firm is operating in, it might purchase its inputs and sell its outputs to a market that is constituted by other firms, individuals or groups of individuals. If the market as an institution does not exist or exists only on the input or output side, the input factors and/or the services or goods the firm delivers might be prescribed by a central planning authority that is constituted by a state organization or parent firm.

The transformation process that takes place within a firm is mainly determined by the services or goods the firm wants or has to supply.

It may look completely different for industrial or trade firms, banking institutions, insurance companies or economic units like agricultural co-operatives, to name a few.

The environment and the more technical nature of the transformation process constitute the framework within which the planning and organization, information and decision functions or factors of a firm effect, supervise and control the combination and transformation process. To a very large extent, it is the very nature of these factors that determine the objectives and goals of a firm

Figure 1.8. Input and output of a firm



ECONOMICS

The traditional economic theory of the firm (viz. [64], [54], [30], [81]) was originally a collection of hypotheses relating, for example, a firm's objective function and its inputs and outputs by a set of algebraic equations. These equations possessed a completely deterministic structure. Thus, it was possible with absolute certainty to attribute a

certain profit made by the firm to the quantities sold and purchased, the sales prices of its products and purchase prices of its inputs. Under a very special set of assumptions it was possible to calculate the necessary inputs and outputs of the firm that maximized its profit. The theory of the firm originally described a so-called autonomous system: the equations did not explicitly depend on time. The theory mainly related static or stationary values of the input variables, output variables and the profit function.

Every single assumption of this theory has come under severe attack, mainly because it was felt that it could not supply realistic models of actual firms, either for descriptive, predicative or explicative purposes (viz. [102], [18], [16], [83]). As a consequence, the theory has been enhanced. First, it was made dynamic to allow for a description of transient states of input and output variables that had to be taken care of whenever lags and leads in the production and transformation process were observed. Furthermore, the objective function was generalized (e.g., sales, long-term rentability) (viz. [12], [66], [45]). Secondly, appropriate methods were used to describe inequality relations that were found to be important within the firm, but also with respect to the markets surrounding the firm (viz. [31], [37], [38]). Third, problems of risk and uncertainty connected with the model structure and its parameters have been identified and tentative solutions to certain classes of problems have been discussed by a number of authors (viz. [111], [109], [91], [62], [63]).

BEHAVIORAL AND ORGANIZATIONAL THEORIES

Within the classical theory, the firm may be viewed "... as an impersonal 'black box' which responds automatically to changes in the external world" [18, p.2], once a criterion of utility (i.e., profits, costs, sales) has been defined for the firm as a whole. As Cyert and March [30, p.16] point out "... there is no attention to, or interest in, the actual process by which firms reach decisions." If one distinguishes with Gutenberg [54, p.131] the rational, irrational and creative executive elements underlying every use of the production factors, then one sees that the classical theory and its extensions are entirely based on

rational decision making. In its original form, it assumes that

> " ... the firm has perfect information on costs, markets, etc., or, more precisely, that all information is immediately and costlessly supplied to a central decision maker -- an entrepreneur -- whose decisions after receipt of this information are also instantaneously put into effect"

(Bonini [18, p.6]).

It is these observations that caused, among others, Mattesich [78,79] and Holt-Modigliani-Muth-Simon [66] to investigate directly the nature, collection and use of accounting information that firms base their decisions on. Cohen, Cyert and March [28,30], Bonini [18] and, to some extent, Forrester [43], discuss various possibilities of how decisions and the flow of information within a firm are influenced by the organizational structure of the firm and the behavior of the persons belonging to such a structure. Especially, Naylor has noted that these organizational and behavioral findings had only a small impact on the corporate modeling work actually going on [81, 83]. However, they gave indications in which areas computer-based and formal models could be used and where formal models had to be combined with the user's mental model of the firm.

COMPUTER SCIENCE, TECHNOLOGY AND QUANTITATIVE METHODS

All the developments mentioned thus far have in common a more complex picture of the firm. One may conclude that a realistic picture of the firm and its practical use for descriptive, predicative and explicative purposes would possibly be based upon a great many measurements of the firm's variables, a variety of elementary as well as non-elementary equations and logical relations to represent a firm's structure. There would be a great number of possibilities to evaluate these relations numerically. It has been noted before that the ability to experiment numerically with models of hypothetical firms and, afterwards, with models of real world firms, would not exist without the progress made in the computer sciences and technology.

The increasing number of at least partially computerized information and planning systems in modern firms makes it possible to run a model that, to a large extent, is based on data of the firm. These are automatically collected, processed and filtered for modeling purposes. Developments of computer hardware, such as storage devices and input as well as

output facilities (e.g., terminals or light screens), made communication with a model easier from a technical viewpoint. Recent software developments, in problem oriented programming languages suited for business as well as scientific modeling and special purpose corporate simulation and planning languages (CSPLS) made user-model communication much easier from a symbolic, notational and conceptual viewpoint. The latter development was initiated by Forrester and co-workers [43, 90] with the construction of their continuous system modeling language DYNAMO in 1961. More recent operational models and languages are based on a conceptual framework and modeling system first developed by Lande and co-workers [74,75] up to 1968.

The application of advanced operations research or econometric methods in corporate modeling is today still more the exception than the rule. Nevertheless, linear programming techniques have been used in a number of instances [1, 11, 35, 56, 36, 106, 108]. One would also expect that searching and hill climbing methods as well as variational methods must become increasingly important if corporate modeling activities are to concentrate more on constraints and production modeling (viz. Rosenkranz [95]). One may expect a similar emphasis with respect to the use of econometric estimation and verification techniques, especially in the marketing area. Multiple regression techniques seem to be used quite frequently already.

MODELS OF HYPOTHETICAL AND REAL WORLD FIRMS

Although real world models seem to be predominant today, models of fictitious firms have played an important role in the past and probably will continue to do so in the future. Two explanations for this observation seem to be available.

On one hand, the construction of a corporate model for a real world firm is by its very nature a process that strongly interferes with the information, planning and decision functions in a firm, mostly at a higher management leve. A model of a fictitious firm may be viewed as a valuable means for the development of a conceptual framework and a methodology for real-world applications. The construction of "throw away models" helps to avoid many failures due to premature disturbance of the firm's internal structure. Ansoff has noted that the trial and error method in planning should be replaced by a tool for planned learning

[6, pp. 41-42]. A computer-based corporate model may be used for trial and error experiments in a laboratory environment.

If one compares the models of hypothetical firms that were constructed at the beginning of the sixties by Forrester, Bonini, Cohen, Cyert and March or Mattesich with the real world models that were described some five years later in the literature (Gershefski, Jackson-Stephenson-Townsend), one sees that most models seem to fit into the conceptual framework originally outlined by Mattesich [78]. It is hard to identify any causal relationship between Mattesich's work and the type of model that today without a doubt is met most frequently in practice, but the coincidences are quite remarkable. Left alone, they already justify the construction of models of hypothetical firms. In the early sixties, a great number of industrial firms possessed a formalized planning and budgeting procedure. Mattesich's work showed, in principle, how the data, variables and equations thus generated or defined could be used to construct corporate financial models. Similar financial models form the "hard core" of many running and implemented models today. At the same time, Mattesich clearly indicated the links between budgeting oriented financial submodels, management science production models and stochastic econometric models describing firm-market interrelationships.

The fact that models of hypothetical firms based either on a dynamic theory of the firm or on organizational, behavioral or engineering concepts have had considerably less impact should not lead to the conclusion that these models do not possess any practical relevance. On the contrary, some of these models in which subjective definitions and estimates play a predominant role, can be understood as abstract descriptions of real world phenomena. To some extent, the fact that work has just begun on subjectively estimated and structured models, especially in the areas of investment and research and development, has prevented real world applications of the approaches mentioned above. As Hertz puts it "... subjectivist probability viewpoints have been gaining in usage, as problems in everyday life seem to require normative rather that descriptive decision making approaches [63, p.10]." Planners urgently need a methodology for modeling and controlling large systems with changing and uncertain structure in which subjective estimates play an important role. It is quite likely that the first applications will be with hypothetical firms, before the results in an applicable form diffuse into industrial applications once again.

COMPLETENESS AND BOUNDARIES

The corporate modeling approach does not seem to be limited by the nature or the legal setup of a company [49, 52, 85]. The literature contains descriptions of models from all three branches of an economy: models seem to be used by agricultural cooperatives, service and public utility companies like banks, traveling agencies, trade firms and state-owned electricity companies. However, most references either implicitly or explicitly deal with the multi-product industrial firm which is surrounded by markets, where it purchases its imputs and sells its outputs [85]. The following discussions will mainly deal with this type of firm.

There are several reasons for this course of discussion. First, based on the ranking according to criteria like values generated or number of people employed, this type of firm appears to be very important. Secondly, for other types of firms, the activities in the area of finance, production and marketing are specialized or even missing. Therefore, one can perhaps expect a more general methodology for corporate models if we concentrate on the multi-product industrial firm.

FUNCTION

A corporate model not only attempts to describe the finance, production and marketing activities of a firm, but also tries to integrate models or submodels from these functional areas. Although the description of the marketing and production area will often employ models of physical flows, in the following sections this will not be used as a prerequisite. A model which describes the marketing area, e.g., by sales, or the production area, e.g., by costs, using hypotheses expressed in financial terms will be regarded as a corporate model as long as aspects of all three areas are dealt with and the organizational unit described is of relevance for the total firm. This is illustrated by Figure 1.9 which shows the commonly encountered task oriented structure of a company using divisions or strategic business units. Both a divisional or a total company model will be considered as corporate model.

Figure 1.9. Functional structure of a company

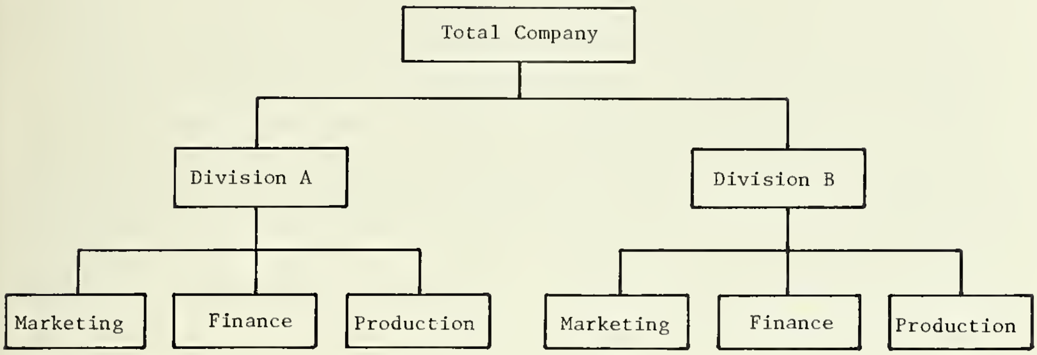
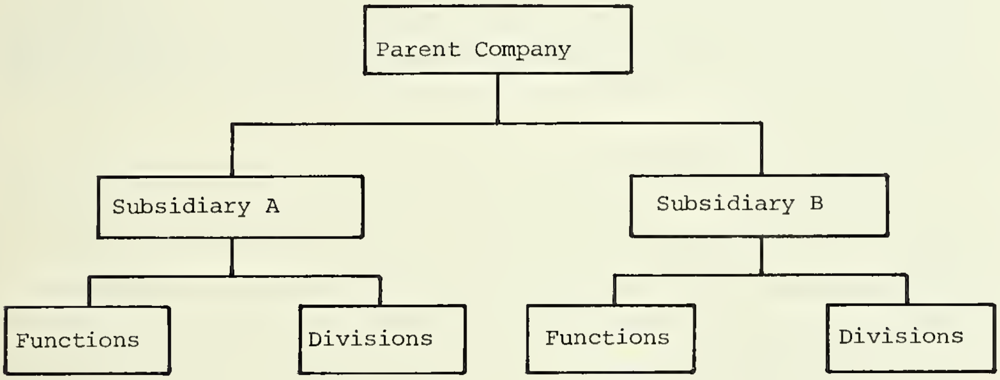


Figure 1.10. Organizational and legal structure



ORGANIZATION AND LEGAL STRUCTURE

A similar approach will be chosen with respect to organizational aspects. A corporate model should be a model of a complete firm. Ideally, it describes an entire firm and possibly integrates submodels dealing with several organizational subunits. However, this will again be no prerequisite. Figure 1.10 shows the familiar structure of a parent company holding several legally independent subsidiaries. All three, a parent company model, a subsidiary company model, or even the model of a division within a subsidiary company will be considered corporate models as long as they include the three functional areas.

RELATION TO THE ENVIRONMENT

Several authors have conceived the firm as an open, goal-oriented socio-technical system (viz. e.g, Ulrich [112], Ackoff and Emery [4]). As Shortell writes "the relationship between an organization's environment and its goals and technology is complex and not easily disentangled. Each affects and is affected by the other. On the one hand, it is possible to argue that an organization's goals and the technology are derived from and determined by its perception of the environment. On the other hand, it can be argued that an organization's environment is in large part circumscribed or bounded by the goals and technology chosen by the owners-managers [101, p.282]."

Regarding its mathematical structure and use, a CSPM may be understood as a one person game against nature (viz. Theil [109, p. 386]). The decision maker or model user specifies actions and policies which are input to the model. The model represents the environment and internal structure of the firm and possibly interactions between the two. Its response follows from the input and is, in principle, indifferent to the input. The environment does not react in a purposeful fashion or follow a certain strategy. It will be shown that this closed system approach, in practice, is more flexible than one would conclude at first sight. The user of a CSPM is able to assume different environmental conditions or the model may be used like a model of an open system, although analytically it is closed.

The environment, e.g., an economy or an industry, is in general not described by a corporate model. It has, however, been noted that

macroeconomic models may be linked to corporate models. With specific industry models the situation is different and the construction of a corporate model may not only require the modeling of the links of a firm to an industry, but some industry modeling itself.

It has been noted that corporate models are not based on new microeconomic theories. Although elements of budgeting theories of the firm [78, 26, 55] are most frequently used with CSPMs concepts of behavioral or organizational theories are employed if models are built, implemented and used. With respect to the type of variables, relations and hypotheses used in a formalized corporate model, such theories, as noted before, have had only a very limited impact. In part, this fact may be explained by the difference between programmable and non-programmable elements of a model. One might thus distinguish between formalized and purely mental models of a firm.

The following chapters will concentrate on formalized model building. Factors of a non-economic origin are assumed to have economic effects and will in most cases be described in economic terms. This represents the present status of corporate model building. If one discusses questions of model integration, implementation and use, it should be remembered that many behavioral and organizational variables are implicitly described which are not part of the formalized model structure.

GOALS, OBJECTIVES AND EVALUATIONS

People involved in a corporate modeling project, be it as sponsors, users, or model builders, have goals and operational objectives which are not easy to extract from the literature or from surveys. In their survey of existing corporate models, Naylor and Schauland show that, in most cases, executives at the top of a company's hierarchy are directly or indirectly sponsors or users of the model [85]. This should explain to some extent why corporate models are so widely used today. Grinyer and Batt remark in this context that "... one should face the fact that objectives of top management are usually implicit, multiple, often incommensurate or conflicting, and change with the balance of political power within the boardroom and with environmental influences which bear upon senior executives. It is rarely possible to find an explicit objective function, in strategic decision taking, that will be a true reflection of the goals of the board, let alone stable over time [51, p.151]."

Gershefski finds that apart from manpower savings and the reduction of clerical planning work "... the hard dollar benefits of a model are difficult to measure [49]." Naylor and Schauland obtained the following descriptions of benefits in their survey [85]. (viz. Figure 1.11).

Figure 1.11. Benefits of corporate models [85]

Benefits	Percentage
Able to explore more alternatives	78
Better quality decision making	72
More effective planning	65
Better understanding of the business	50
Faster decision making	48
More timely information	44
More accurate forecasts	38
Cost savings	28
No benefits	4

Respondents were allowed to designate several benefits. It is interesting to note that "Cost savings" are the only benefit which may directly be related to a classical criterion of economic utility.

Since the objectives of the model sponsors or users should have a very direct influence on how a model is technically used, it is not surprising that models are more often employed as alternative testers than alternative selectors (viz. Dickson, et al. [36, p.59]). The latter use would require an objective function and a model solution employing optimization methods.

Both Gershefski and Naylor/Schauland found that some five percent of the models in their sample were pure optimization models. In most cases, linear programming seems to be the solution method employed. Grinyer and Wooller [52], Grinyer and Batt [51] and Dickson et al.[36] find higher percentages for optimization models. Both Naylor and Schauland and Grinyer and Wooller find that between ten to 20 percent of the models make use of both optimization and alternative testing or simulation. It seems that the simulation concept for a total model does not exclude the use of optimization in submodels.

SOME TYPICAL INVESTIGATIONS

The following list of questions investigated with corporate models was compiled mainly from published conference proceedings and survey articles [19, 20,99, 53, 97]. The questions are by no means exhaustive, mutually exclusive or representative. But they give an impression of the scope of corporate modeling applications and the difficulty involved in determining an objective function for a model or a specific investigation.

CORPORATE FINANCIAL MODELS

- What is the effect of different interest rates and currency exchange rates on the income statement and balance sheet of the firm?
- What effects with respect to the financial position of the firm could an acquisition or merger with another firm have?
- Should the firm produce and sell a certain product, purchase and sell the product or not get involved at all?
- How will the income statement, the balance sheet and cash flow develop for several operating divisions? What will be their net profit contribution?
- In which range will the return on investment on various projects and units lie?
- How should projects be financed if there is a great number of projects, financing possibilities, but also financial restrictions (e.g., debt/equity ratio).
- What is the nature of the conditions that must be fulfilled if the total sales of the firm at a certain time are supposed to be higher than a certain budget value?

CORPORATE MARKETING MODELS

- How do certain states of the national or world economy influence sales of the firm on one side and purchase prices of the production factors on the other?
- What do price demand or supply relations on the output or input side of the firm look like? What are the effects of price/cost changes on sales?

- What is the effect of advertising and distribution expenditures on sales? What marketing strategy can and should the firm follow?
- What will the absence and fluctuation rates of the employees of the firm be and what effect will they have?

CORPORATE PRODUCTION MODELS

- What will be the demand for the end products of the firm at various locations and different times?
- What is and will be the unit marginal income for a certain production, transportation and sales allocation?
- What are the effects of different pricing policies?
- How will future raw material prices and quantity restrictions imposed on the availability of the production factors influence output by quantity and value?
- Where should the firm construct a new plant?
- What impact can a future change of a production technology have?
- How should the firm set inventory levels?

GOALS AND OBJECTIVES IN THE LITERATURE

The question of goals and objectives of the firm has been discussed thoroughly in the literature. The profit maximizing or optimizing firm has been the predominant research object of the classical theory of the firm and also of many theoretical investigations and practical applications of operations research and the management sciences. However, similar to the above discussed case of corporate modeling applications, other empirical investigations indicate that firms rarely have a single and explicit goal or an objective function which is to be optimized [18, 30, 102, 16, 17, 60, 61, 41]. This is understandable if one imagines, for instance, the overall goals of a government owned and controlled electric utility company. Regarding its legal structure and its environment, it would be surprising to find a single optimizing objective. Even for the "representative" multi-product industrial firm operating in a market economy, the questions of goals and objectives has many facets. These problems have given rise to extensions of the theory of the firm which

take the following factors into account:

- the nature of the firm's environment;
- the process by which the environment and interactions with the firm are observed;
- the process by which the information thus obtained is stored and remembered;
- the processing of information for decision making;
- the planning process; and
- the implementation process for management decisions (viz. Day [33, pp. 14-16]).

Several authors have discussed taxonomies of goals and decision processes of the firm. Ackoff has introduced the classification into the optimizing, satisficing and adaptive approach which a firm may have with regard to the combination process of its input factors [2,5]. Nutt, in a more detailed manner, distinguishes the following goals and decision criteria:

- maximum efficiency;
- maximum subjective expected utility;
- satisficing goals defined by key or domain decisions;
- satisficing goals set by participants in the decision process;
- unknown goals which are defined by a process of conflict resolution;
- goals of survival and acceptability which are implicit and unknowable.

At the same time, he suggests a number of mental models of decision making to be used with the decision criteria given above [87].

An <u>optimizing firm</u> would look for a combination of its inputs which, in the sense of an objective maximum efficiency, would yield minimum factor requirements. In addition to this economic principle, the optimizing firm may either maximize objectives like profits, rentability or sales or minimize costs. In addition, the subjective weighting of several criteria with respect to a utility scale and the maximization of expected utility would be an optimizing goal (viz. Baumol [12, pp. 45-82], Theil [109, pp. 372-527]).

The <u>satisficing firm</u> sets goals and objectives with respect to its outputs and is quite content if it can assure a combination of its input factors that guarantees that the planning output can be attained [102]. These goals may either be predefined by the firm's top management, be set by participants in the decision process, or be the result of a bargaining

and conflict resolution process. The target approach described by Tinbergen for macroeconomic applications [110, 83] or the mark-up and mark-down decisions incorporated in a model of a hypothetical firm by Cyert and March [30, pp. 137-148] contain many elements of a satisficing approach. Satisficing objectives may follow from a fairly accurate knowledge of the firm's cost structure, but insufficient market information. A mark-up on costs to determine prices is a reactive strategy in this particular situation.

The adaptive firm, finally, operates in an environment with which it strongly interacts. However, the firm is not able to abstract, model or predict these interactions precisely. It is also unable to adapt or adjust to feedback information [5, 13, 14, 43, 6, 59, 33, 116]. As a consequence, the firm's goal is to survive and achieve acceptable combinations of its input factors with respect to uncertain and rapidly changing environmental conditions. The more operationally defined the adaptive firm becomes, the more it strives for decisions which bring it into a robust, flexible and stable state (viz. [92, 58, 59, 69, 33,111]). Ideally, the adaptive firm anticipates possible changes within its own structure or its environment. It either adapts its structure if its institutional or economic survival is endangered or, it directly tries to effect changes in its environment [2].

One may draw several conclusions from this short description of the goals and objectives of the three "idealized" types of firms. In practice one would rarely encounter any pure decision approach within a firm, but rather a mixture of all three approaches. Accepting the economic principle and assuming a firm or an organizational unit which accurately knows the price and restrictions on its inputs, its production process and the price it obtains for its outputs, it is hard to conceive why it should not at least partially optimize. In fact, there is some evidence that the environment of the oil companies until the recent disturbance of the oil markets was close to this idealized situation. This could explain their use of optimization techniques even for corporate modeling purposes [1, 115, 65, 52]. An "idealized" satisficing approach may be found with organizational units of companies who obtain sales or profitability targets and adjust their decisions in such a way that they can achieve these targets. Finally, there are many hedging policies known which a

firm might use to adapt itself to largely unpredictable disturbances of the currency or raw material markets.

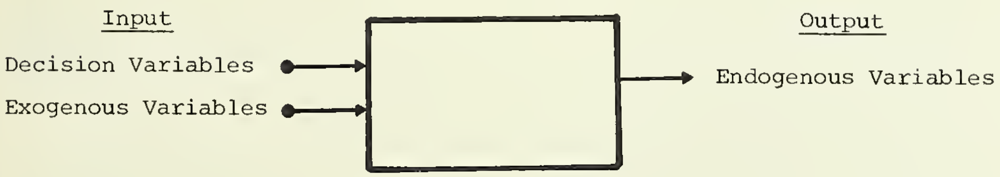
Some have argued that the adaptive firm is not a separate category, since it depends largely on the environment a company operates to determine whether it uses optimizing or satisficing strategies to adapt. Similar arguments may be put forward with respect to the differences between optimizing and satisficing goals. For example, satisficing goals may take the form of restrictions on a firm's decision. According to the economic principle, these decisions may be determined in such a way that an efficient or most economic combination of input factors be obtained.

If a company employs a CSPM for decision support purposes, one should expect that the type of goal and decision criteria has some influence on the type of model solution it is looking for.

TYPES OF MODEL INVESTIGATIONS

A corporate model may be understood as a set of formalized relationships, notable equations, which relate so-called input variables to output variables. An evaluation method or algorithm is used to calculate the values of the output variables for given input variables (viz. Day [33, pp. 17-18]). Both relationships and evaluation method are normally coded for a computer, because, compared to a manual evaluation, economic reasons favor a computer based calculation from given inputs. Figure 1.12 represents this situation.

Figure 1.12. Input and output variables of a corporate model



In agreement with the terminology, the output variables are called endogenous variables. The input variables are subdivided into so-called exogenous and decision or policy variables. The values of exogenous input variables are known and kept constant in a model evaluation. Decision input variables are chosen by the model user to test their influence on the endogenous variables.

Because the significance of these types of variables is largely ingerchangeable, the following sections will use an economic interpretation. The values of the decision variables represent managerial or user decisions, whereas, exogenous variables are defined or set by a firm's environment which cannot be influenced by the decision maker. The reader will notice that in contrast to this definition, a model user in a computer experiment may determine or decide on environmental conditions which he would not be able to influence in economic reality.

From a technical viewpoint, it seems as if corporate models are mainly intended to give answers to three types of questions.

NO EXTERNAL DECISION

The first type answers questions relating to a development of the firm and its surroundings in which possible effects of the firm's policies are not taken into consideration. Questions of this endogenous or "no external decision" type frequently investigate the coupling of variables of the firm to extrapolated macroeconomic variables like GNP or certain raw material prices or simply integrate the firm's planning figures. Also simple data or database evaluations, answers to what Naylor has called "What is?" or "What has been?" questions [84], fall into this category. The same would be true for most optimization models where one of the model relationships may be an objective function. If an optimization algorithm is specified as an evaluation method, it may not need additional external decisions to determine the endogenous variables. After the objective function of an optimization model has been defined, the decision maker has no degree of freedom left to interfere with the model. Sensitivity or post-optimal analysis based on an optimization model, on the contrary, answers questions of the second and third type.

WHAT IF?

The second type answers so-called "What if?" questions. This type of question very often takes the form "What happens under a given set of assumptions if I act in a prescribed way?" A model for this type of question is supposed to give a quantitative answer to a certain sequence or combination of hypothetical entrepreneurial decisions. Alternatively, the model user might simulate different developments of the surroundings of the firm that cannot be forecasted and ask: "What happens to my fixed and current assets in Europe if the money parities change in a certain way?" Provided that the structure of the underlying model is deterministic, i.e., all equations, exogenous variables and parameters are known with absolute certainty, the answer to the questions would either be given analytically or by a so-called deterministic or "case study" simulation (viz. Rosenkranz [93]). With an analytical solution, the output variables of the model that are of interest would directly be expressed by equations as a function of the decision or policy variables. Since in many cases this is not possible due to mathematical reasons, the solution or answer may be generated by an experiment with the model or a simulation. The case study simulation certainly is the experimental approach most often used with corporate models today. In the case that some variables or parameters in a model are only defined with a given frequency distribution the answer to the questions is either given via an analytical solution of the model or - in most cases - by a so-called stochastic simulation. Since answers to "What if?" questions are only based on the history and present state of the firm, and future values of the output variables are calculated or generated on this basis, one mainly deals with a forward solution or simulation.

WHAT TO DO TO ACHIEVE?

The third type of questions frequently asked takes the form "What has to be done to achieve a given output?" This means that the decision maker targets for the endogenous variables and wants to use the model for the determination of decisions that lead up to the predefined target values (viz. [110], [83], [97]). It is obvious that this target approach is more

restrictive than the "What if?" approach discussed above. The answer is not only restricted from the beginning (i.e., past and present values of the model variables), but also from the end (i.e., end or target values of the output variables) or in-between. In the case where feasible values for the output variables exist, they may again be found either analytically or by experimentation with the model. The underlying model structure might either be deterministic or stochastic. The solution or simulation can now either be affected forwards based on the initial values, or backwards based on the target values. If the initial values of the output variables are not prescribed, one usually carries out a backward solution or simulation.

TYPES OF MODEL SOLUTION

From a technical viewpoint, the problem of determining a model solution is identical for all types of investigations: the output or a number of unknowns has to be computed from the inputs. Note that in a "What to do to achieve?" investigation, a part of the economically interpreted output is input to a solution.

Thus, one may have three types of results to the problem of model solution: there may be one unique solution, several or even an infinite number of solutions, or no feasible solution which would allow the calculation of the unknowns from the input.

In the case of the most freqnently discussed "What if?" investigation this fact is only disguised by the practitioner's habit of specifying exactly the number of decisions required to achieve a unique model solution. However, the other two cases are also of interest. One would obtain more than one solution if too few decisions are taken and no feasible solution if too many or possibly conflicting decisions are taken. A corporate model is generally used as an alternative tester with respect to those decisions which cannot be set on a priori grounds. The problem of a decision conflict in practice seems to be solved outside the model before the decisions for a "What if?" investigation are specified.

The same arguments hold for "What to do to achieve?" type investigations. A user may specify not enough or too many targets to allow a unique solution in the decision variables. Since an investigation in the "no external decision" situation neither uses decision variables nor

target values for the endogenous variables, the cases of under- or over-determined solutions are likely to occur due to model specification error.

TYPE OF INVESTIGATION AND GOALS OF THE FIRM

It has been argued that in practice one would rarely encounter any of the "idealized" firms described above. Similarly, one may argue that there does not exist a one-to-one correspondence between the type and goals of a firm and the type of investigation it chooses to evaluate a corporate model. It is possible to relate an optimizing firm to the "no external decision" type investigation. The satisficing approach may be related to "What to do to achieve?" type investigations, since targets must be specified. "What if?" type investigations require minimum assumptions with respect to goals, objectives, targets and the environment of a firm. They may tentatively be related to the "idealized" adaptive firm. If an association is at all possible then the most frequently mentioned benefits in Figure 1.11 should be related to flexibility goals characterized by the "adaptive" firm. Assuming that goals of survival and flexibility are today most frequently found in practice (viz. Steers [104]) this would explain the fact that "What if?" investigations are most frequently employed by users of corporate models.

One should remember that the state of information model builders and users possess about the internal structure and external environment of their company will determine, in part, which approach is chosen. If the model structure very accurately represents reality then the target approach may be combined with the objectives to minimize target deviations. Also, the adaptive approach may be combined with the objective to maximize flexibility or to obtain a time optimal adjustment (viz. Simon [102], Gupta and Rosenhead [92], Eilon [40], Jacob [69], Eliasson [41]).

OTHER FACTORS INFLUENCING THE TYPE OF MODEL

It has been mentioned that goals and the environment of a firm influence the type of corporate model and investigation it is used for. There are a number of other, not necessarily independent, factors which should be mentioned in this context. They are notably:

- the organizational unit or user within a firm for which a model is built and who controls it;
- the background and organizational status of the model builders; and
- the intended use of the model or the type of planning it is supposed to support.

The survey results cited earlier indicate that corporate models are most often used to support middle-range planning activities in the financial area. As a consequence, the hard core of these models is likely to be a budget simulation largely based on financial identities. This tendency is reinforced if the model is constructed for the finance or control function of, say, a bank or insurance company. In the case where the model is built by financial analysts, it is not very probable that advanced techniques of econometrics and operations research will be used (viz. Jackson, et al. [67, 68], Chervany, et al. [25], Archer [8], Buchinger [23], Lanstein [76], Rosenkranz and Pellegrini [96]).

The production department of an operational division of a large international firm or firms which purchase their inputs or sell their outputs to different regional markets will have a tendency to model physical flows. Some may even build their model around the hard core of some optimization submodel that takes care of resource planning (e.g., Abe [1], Dickens [35], Bard-Woo [11], Des Jardins and Lee [34], Hamilton and Moses [56], Thaler [108], Kiffe and Steinbach [71], Rosenkranz [95], Szyperski, et al [106]). If the model builders are operations research analysts, it is plausible to assume that this will increase the tendency towards this type of model.

In the marketing area of a firm which produces consumer products, one may expect to find econometric models and simulation techniques more often applied than e.g. in the production area (viz. Wagle [115], Davis, et al [32], Aurich [9], Kotler [73], Rosenkranz [94, 97], Seaberg and Seaberg [100]).

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Methodological and Practical Problems

SOME ANALOGIES[1]

A good intuitive understanding of what corporate models deal with and where problems in their numerical description arise may be obtained from a mechanical analogue as is shown in Figure 2.1. A number of suspended masses interconnected with elastic and friction elements (e.g. springs, friction-clutches) are shown.

Some of these masses are connected to moveable walls. Any experiment with the mechanical system shown in which one of the masses is displaced would result in a movement of the other masses that are directly or indirectly coupled to the original one. Because of their large mass, the movement of the walls would perhaps not be observable, if only the suspended masses are in motion.

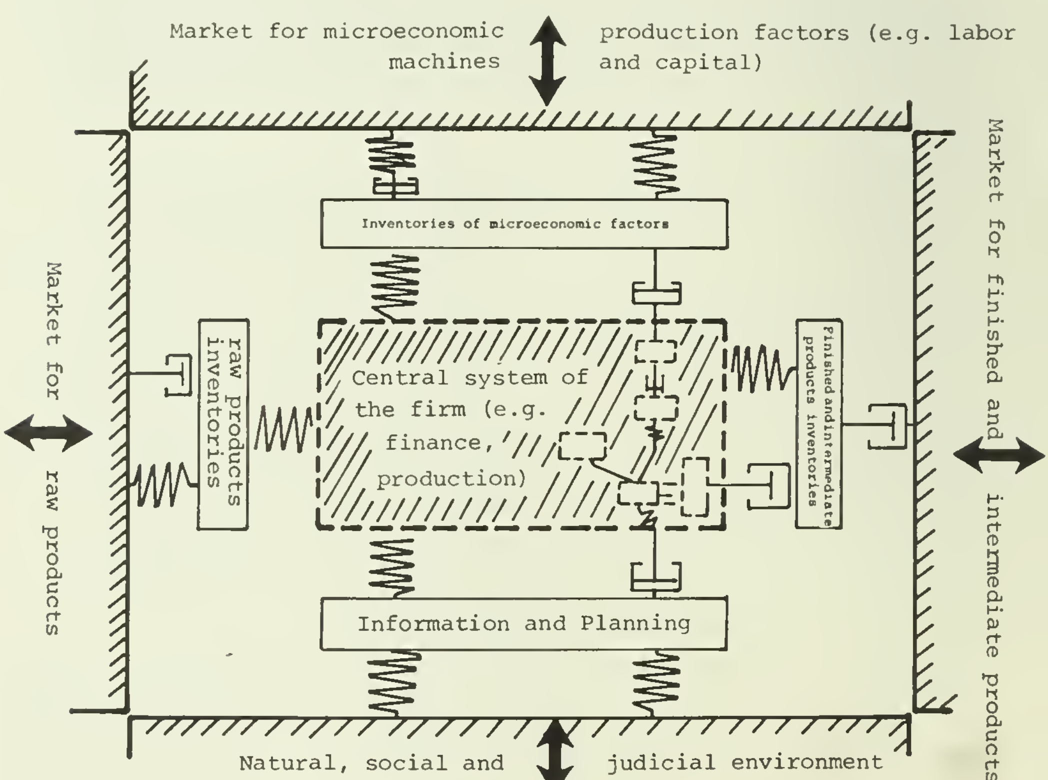
In the model, the masses shown represent the variables that describe a firm. The connecting elements describe the relations between the variables. Thus the masses represent the variables of the firm in the area of finance, production and marketing. Financial variables could be the current or fixed assets of the firm, its inventories of raw, intermediate and finished products by value or the cash-flow. Examples of variables met in the production area could be inventories by quantity, capacities or work force by number. Marketing variables could be the number of sales representatives employed by the firm, advertisement and distribution expenditures expressed in meaningful and measurable units or the number of sales outlets controlled by it.

The walls in Figure 2.1 represent the macro-environment of the firm, examples being a market for raw materials, a market where the firm sells and purchases its intermediate and finished products, a market for labor

and capital as well as a surrounding or "larger external environment" (Boulding [23, pp. 15-15]) called the natural, social and judicial environment. Increasing state interference and regulations concerning pollution and safety problems, distribution of profits, labor hours or a changing work-moral or "codetermination" of the employees ("larger internal environment," Boulding) and the evolution of new political communities and trade areas are just some examples of the importance of this environment.

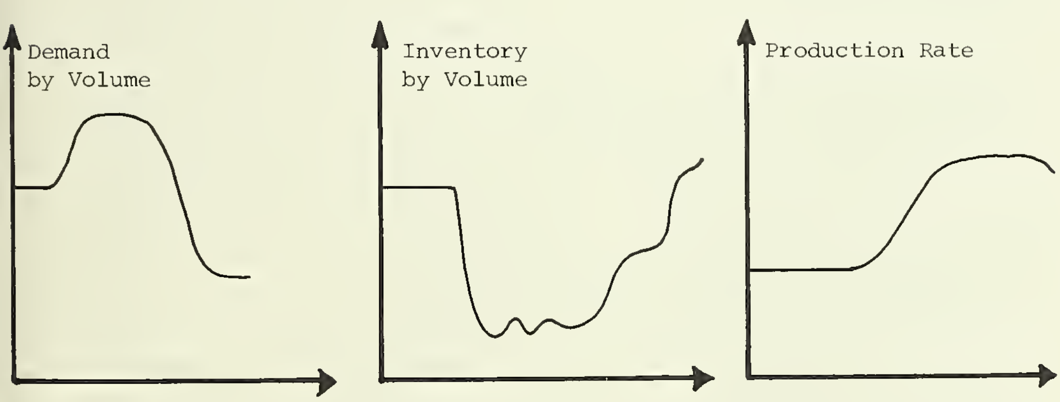
The masses may - in the accounting sense - represent flow variables (e.g. cash-flow) as well as stock variables (e.g. assets). Their position measured with reference to a one-dimensional scale indicates the value the variables have for a certain configuration of the mechanical network. For a high inventory level, the position of the mass denoted by "raw product inventories" would be different from its position for a low inventory level.

Figure 2.1. Mechanical analogue to a corporate model showing the firm coupled to its macroeconomic environment



One sees that the central part of the mechanical model is not directly coupled to the walls, but to intermediate masses. These are meant to represent inventories in production factors which the firm keeps in order to protect the central system from sudden shocks and disturbances in its environment. If one of the walls is moved by an externalforce or if the internal structure of the system is changed, then the mechanical system which might have been in equilibrium, would react to such disturbances with positively or negatively damped oscillations or aperiodic adjustment. One can observe a similar behavior in economic reality. For instance, a sudden increase in demand for finished products would correspond to a movement of the right wall. One would observe an abnormal decrease of inventories. This would perhaps lead to an increase in the production rate and, due to some retarded coupled relationships, to an overshoot effect in inventories at a later time if demand decreases. A similar dynamics was observed before and during the last recession, e.g. in the textile industry. High inventories had to be financed under a relatively tight money market and brought a number of firms into financial difficulties. Figure 2.2 shows an example how the variables indicated above could develop in time.

Figure 2.2. Sales-inventory-production system



It is thus easily understood that inventories normally dampen and delay disturbances which come from the firm's external environment. The exact nature of the interaction of the variables is determined by a number of factors, such as the nature of the product, the customers served, the technical equipment used in the production plant.

BEHAVIOR OF THE FIRM

The time paths as shown in Figure 2.2 are normally influenced to a large extent by the behavior, goals and objectives of those functions of the firm that control the system or parts of its. This has already been discussed previously in Chapter 1.

A satisficing firm or inventory control function would define maximum and minimum inventory levels and only act, e.g. adjust the production rate, if the observed inventory level is outside this range. Engineers would describe this type of behavior by the term "bang-bang control."

The prototype optimizing firm would concentrate on an investigation of change-over costs for the inventory stage and demand forecasts on the input side. Based on this information, it would then choose its actions in such a way that either total costs, profits or a multi-criterion objective function connected with the operation of the system would be minimized or maximized for a period or over a planning horizon.

The adaptive firm would perhaps behave quite similarly to the optimizing firm, but would, in addition, investigate possibilities of smoothing the demand with its pricing, distribution or advertisement policy, or diminish the system's inertia and increase its flexibility either by the introduction of a new forecasting and control technique or new equipment with shorter change-over times.

Similar behavior may be observed in quite different areas: the decision of a firm to change its legal structure might be a reaction, adaption or "optimization" with respect to changes in its judicial environment. The introduction of "sliding" work-hours in a variety of firms may be viewed as a reaction or adaption of those firms towards urban traffic problems and the changing work moral of its employees.

A TERMINOLOGY FOR DISCRETE MODELS

In the intuitive mechanical model of Figure 2.1 the positions of the individual masses at a certain time correspond to values of inventories, accounts, capacities, production levels and the like within the firm. The positions of the walls characterize the quantitative values of a set of macro-variables that describe the surroundings of the firm. These variables may be called state variables.

MODEL VARIABLES

Although in the physical model a state is uniquely defined by the automatic evolution of the state variables from their initial values, in the corporate model state changes can be affected by the variation of so-called decision or policy variables. Their values are not automatically supplied or generated inside the model, but have to be specified from the outside, either by the model user or the decision maker. Typical decision variables in a corporate model are, for example, security stock levels, stock orders, advertising expenditures, investment expenditures, dividends or prices. The same variables might be state variables in other models provided that they are automatically determined according to a hypothesis specified within a model.

Among the state variables of a corporate model, one may further distinguish between so-called exogenous variables and endogenous variables. The first group of variables is not determined within the model but like decision variables - specified from the outside. In contrast, endogenous variables are determined within a model, once the values of the exogenous and the decision variables have been supplied. Unlike decision variables, exogenous variables cannot be influenced or set by a model user or decision maker. In the mechanical model, c.f. Figure 2.1, exogenous variables are represented by the walls. Their mass and inertia do not exclude an interaction with the variables determined within the model, but make it negligible in one direction, reactive in the other. Variables in a model are exogenous either by meaning, as has been described above, or by definition. The latter case can occur in a number of situations: first, if the corporate model consists of several submodels,

that are only loosely connected, a model user might run these submodels in an isolated fashion. He would then treat some endogenous variables as exogenous variables and would use the endogenous variables of one submodel as exogenous input into another model and vice versa. Such a partition into submodels is permissible only if the interaction is very loose or if several iterations between the models are performed. Secondly, one may imagine cases in which a model contains more endogenous variables than (linearly) independent equations that relate them. In this case, a user may treat some of the endogenous variables as exogenous or decision variables and assign values to them himself. The model would then be solved for the remaining endogenous variables. Underdetermined models of this nature are frequently encountered in resource planning and solved by mathematical or goal programming techniques. With these techniques the user assigns values to the variables not determined that maximize or minimize some [illegible] of utility or loss. Instead, he might assign target values to the variables and solve for the remaining endogenous variables [109, 139]. Third, endogenous variables that appear with a time lag in an equation are treated as exogenous variables. On the one hand they are determined within a model, once their initial values have been supplied by the user, on the other hand, they are predetermined, i.e., known or already calculated if a model is evaluated at a certain time. An example is given by eq. (2.1):

$$S_t = 0.25\, S_{t-3} + 0.3\, S_{t-2} + 0.45\, S_{t-1} \quad . \tag{2.1}$$

Sales S_t at time t is a function of sales S_{t-1}, S_{t-2} and S_{t-3} in the three previous periods. The endogenous variable S_t may be calculated for all times $t \geq 3$ provided that the initial values of the predetermined variables S_{t-3}, S_{t-2} and S_{t-1} are given. These could correspond to the sales values S_0, S_1, and S_2.

Altogether one may represent a deterministic corporate model by a number (m) of dynamic equations

$$f_{it}\ (\underline{Y}_t, \underline{Y}_{t-1}, \underline{X}_t, \underline{\Theta}_t) = 0, \quad \begin{array}{l} i = [1, m] \\ t = [1, n] \end{array} \tag{2.2}$$

that relate vectors of endogenous variables $\underline{Y}_t^T = [y_{1t} y_{2t} \ldots\ldots y_{kt}]$, predetermined variables $\underline{Y}_{t-1}^T = [y_{1t-1}\ y_{2t-1} \ldots\ldots y_{kt-1}]$, exogenous variables $X_t^T = [x_{1t}\ x_{2t} \ldots\ldots x_{\ell t}]$ and decision variables $\underline{\theta}_t^T = [\Theta_{1t}\ \theta_{2t} \ldots \theta_{ht}]$. [2]

The model may be described by a system of algebraic and first order differential or difference equations, because higher orders in the endogenous variables or the decision variables can be reduced to first order expressions by the introduction of proxy endogenous variables (Baumol [13, 77]) and redefined decision variables (Fan, Wang [49, p. 38-39]). Lagged exogenous variables may be treated as new exogenous variables. The variables $\underline{\Theta}_t$, $\underline{X}_t$ and the initial values $\underline{Y}_0$ or final values $\underline{Y}_n$ are the input to a model for a "What if?" investigation, whereas, the output Y_t follows from a forward or backward solution of eq. (2.2). In case that the system is underdetermined - i.e., there are less independent equations than endogenous variables - or alternatively if the system is overdetermined, one has to supply additional criteria on how the solution should be effected. A mathematical programming solution would be an example of the first type, a least squares or Tschebycheff approximation solution an example of the second type. One of the model equations would define a so-called objective function for these cases.

DISCRETE AND CONTINUOUS MODELS

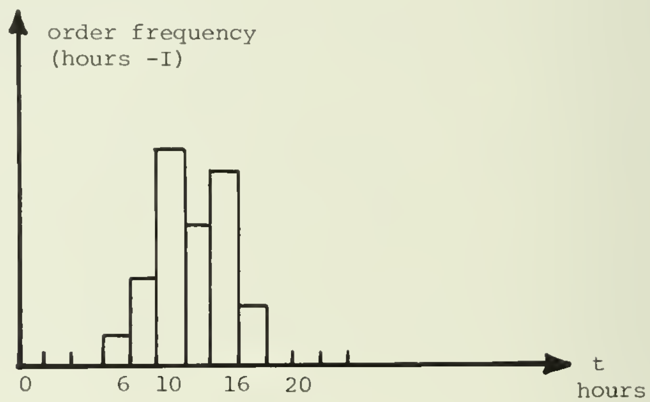
The indices used with the above definitions imply that one can distinguish the variables. This means that variables y_{it} and y_{jt} are differently defined for $i \neq j$. The lower case letters i and j could indicate different sales regions, business units, production plants or accounts. One can thus say that the variables of a corporate model are in general discretely defined with respect to "location" aspects, such as markets, customer groups, subunits of the firm and areas of bookkeeping. Variables may, however, by aggregates.

In contrast to the discrete definition of model variables with respect to location aspects, they may either be continuously or discretely defined with respect to time.

The interaction of state and decision variables in economic reality clearly does not only occur at the end of hours, days, months and years. Customers may order products with varying frequency during a day (Figure 2.3). Financial transactions may take place at various times and one could imagine the definition of a probability of such a transaction happening in an infinitely small time increment. A corporate system should

therefore be regarded as a continuous system with respect to time. In contrast to the real interaction, the firm may either be discretely or continuously described in a model.

Figure 2.3. Order frequency distribution



A survey of the corporate modeling literature reveals, however, that only models based on the Industrial Dynamics methodology [51,89,132] seem to have continuous hypotheses underlying them. Most of the CSPMs known today are discrete models. With the exception of a very few models in which the firm is conceptually understood as a network of queues (e.g. [98, pp.326-329]) discrete corporate models are discrete constant increment models. This means that state changes in the model only occur at natural multiples $t_j = j \Delta t$, $j = [1,n]$, of a base time interval Δt. The increment Δt is in most applications measured in years, but there is no reason to exclude units like months, quarters or multiples of a year. Times t_j at which state changes may occur are frequently called stages. In the sequel, a lower case letter t used with a variable always indicates that the variable is discretely defined with respect to time and that the time increment Δt is normalized to $\Delta t = 1$. In so-called non-autonomous models, i.e., models that depend on time explicitly, time is treated as an exogenous state variable which obeys the difference equation

(2.3) $$t_j = t_{j-1} + 1 \quad j = [1,n], \; t_0 = 0$$

The linear trend model

$$S_{t_j} = 100 + 10 \cdot t_j \tag{2.4}$$

or

$$S_t = 100 + 10\, t$$

is an example for such a non-autonomous model.

A typical example of a discrete constant increment model is expressed by equation (2.5) in which sales S_t of a product are explained as a function of distributed advertisement expenditures A_t

$$S_t = \sum_{\nu=0}^{t} a_\nu \cdot A_{t-\nu} \qquad (t = [0,n]). \tag{2.5}$$

The corresponding continuous expression is the integral

$$S(t) = \int_0^t a^*(t') \cdot A\,(t - t')\, dt'. \tag{2.6}$$

In both cases, the a_ν or $a(t)$ would be appropriate weighting factors or impulse response functions. Figure 2.4 shows an example for a "pulsed" advertising input. It is discretely coincident, i.e., possesses the same values at natural multiples of a basic time unit for both the discrete and continuous model. The continuous sales output shown is calculated for an impulse response function

$$a^*(t) = \frac{1}{t+1} \quad . \tag{2.7}$$

A discretely coincident output for the discrete model is only obtained if

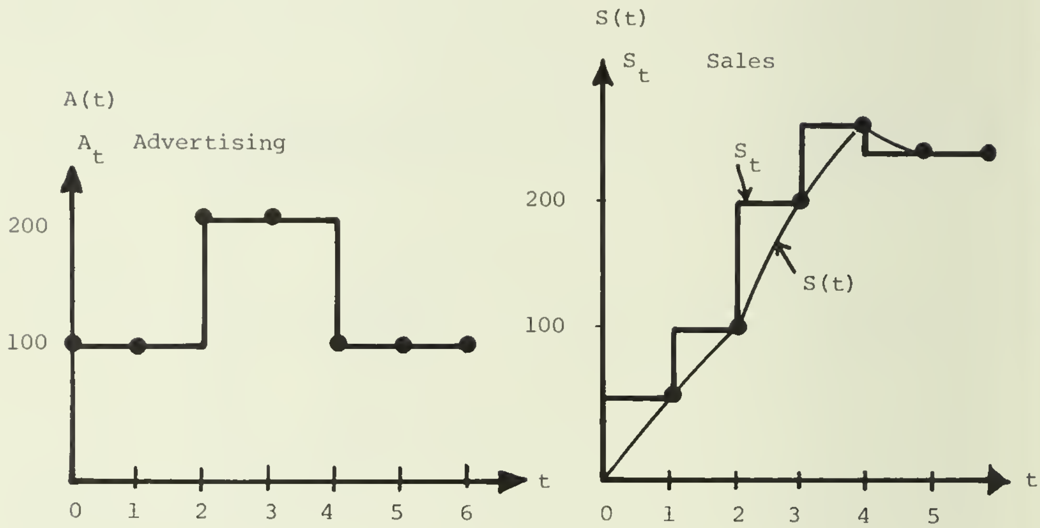
$$a_0 = 0 \tag{2.8}$$

$$a_\nu = \int_\nu^{\nu+1} \frac{d^t}{t+1} \qquad \nu \geq 1 \quad .$$

It is possible to show that for a given continuous model in general a discrete model can be determined with discretely coincident output, provided that the model input is "pulsed" like A(t) in Figure 2.4 (Box,Jenkins [24, pp. 363-367]). Explicitly this means that for this special kind of input a correspondence between the $a^*(t)$ and a_ν in eqs. (2.5-2.6) may be established like it has been shown above. However, models eq. (2.5) and eq. (2.6) are different. For the continuous model, it is assumed that advertising expenditures at every moment have an impact on sales, whereas sales in the discrete model are only influenced by the end

values of advertising expenditures in equally spaced time intervals.

Figure 2.4. Example for discrete and continuous model



The decision as to which kind of model one should use is not based on the fact that a real firm may be viewed as a continuous system. Nor does the existence of a possible correspondence between certain continuous and discrete models lead to such a decision. It seems that the decision only follows from the answer to the question: can one observe and validate the state variables microscopically at any time and define meaningful units for measurement, or does one only observe state variables that are defined as averages and accumulated values or are end values at discrete time with a natural multiple of some constant increment?

In general, it seems that state variables and most decision variables have the latter meaning. Accounting variables are usually observed in regular intervals. The same is true for most of the environmental information or production variables. This implies that any hypothesis about the behavior or the distribution of the variables within a time interval e.g. as expressed by interpolation or spline functions , cannot be validated from the available data. More explicitly this may be understood from Figures 2.5 and 2.6 which show a time series made up of quarterly

measurements of the index of textile production in Western Germany, 1965-1976 and its periodogramm [45, 24, p.36].

The periodogramm may be interpreted as a decomposition of the time series shown in Figure 2.5 into trigonometric functions with natural frequencies. Figure 2.6 shows how strongly the different oscillations appear in the original series. The negative slope of the periodogramm for small frequencies suggests a trend component. The peak at a frequency f = 0.25 is due to the seasonality of the time series.

The periodogramm ends at f ≈ 0.5 which corresponde to a period of two quarters. This indicates, first, that at least three equidistant measurements of the time series are needed to be able to calculate one line of the periodogramm, secondly, that no information about the behavior of the variable is available from the periodogramm for periods of less than two quarters.

The time series was used as an exogenous variable in a marketing model which described sales of CIBA-GEIGY dyestuffs to the German market. No information about the relationship between the sales variable and the "production-index" variable is available in a cross-spectrum unless at least three meanurements of both variables have been collected [11 and refer., 141, 24, pp. 413-416].

The time series shown in Figure 2.5 should not be looked upon as a pulsed input to such a model, since it has only been sampled at constant increment intervals. Therefore, one cannot conclude that for a continuous model, a discretely coincident discrete model exists in general. This means that parameters like the a_ν in eq. (2.5) do not necessarily have continuous correspondents.

Even if one assumes that the input is pulsed, the corresponding a*(t) in eq. (2.6) will, in most cases, not have any immediate economic meaning, because they are not used in practice. This together with the observations that the evaluation of a continuous model would, in most cases, mean more calculation effort that needed for a discrete model, suggests that discrete models for corporate modeling at present seem to be appropriate. The model of an adaptive firm with continuous control so far looks intriguing only as long as one excludes problems of measurement and data collection from the discussion.

Figure 2.5. Time series textile production index West Germany

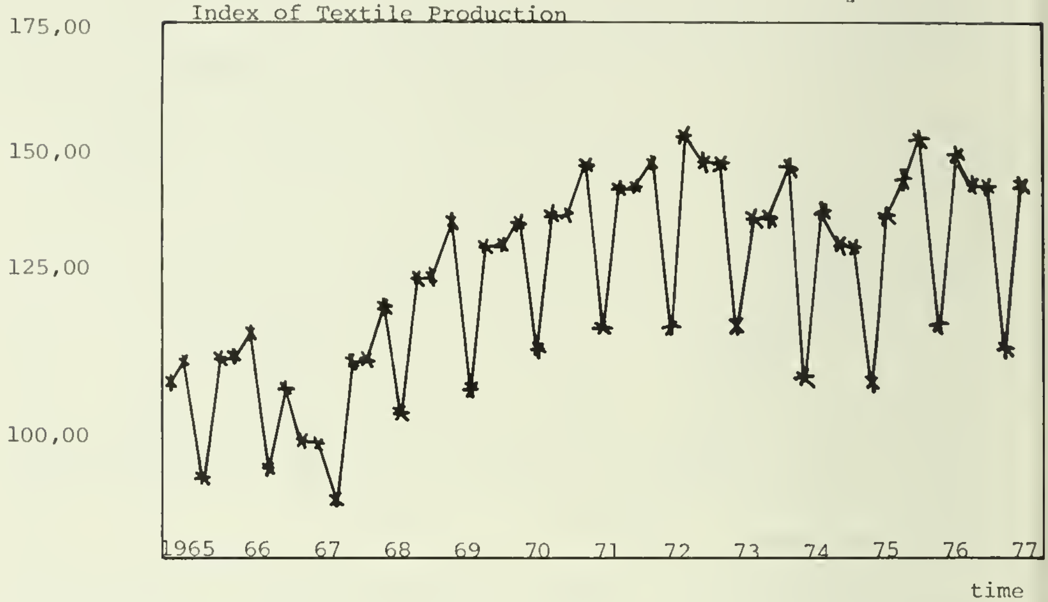
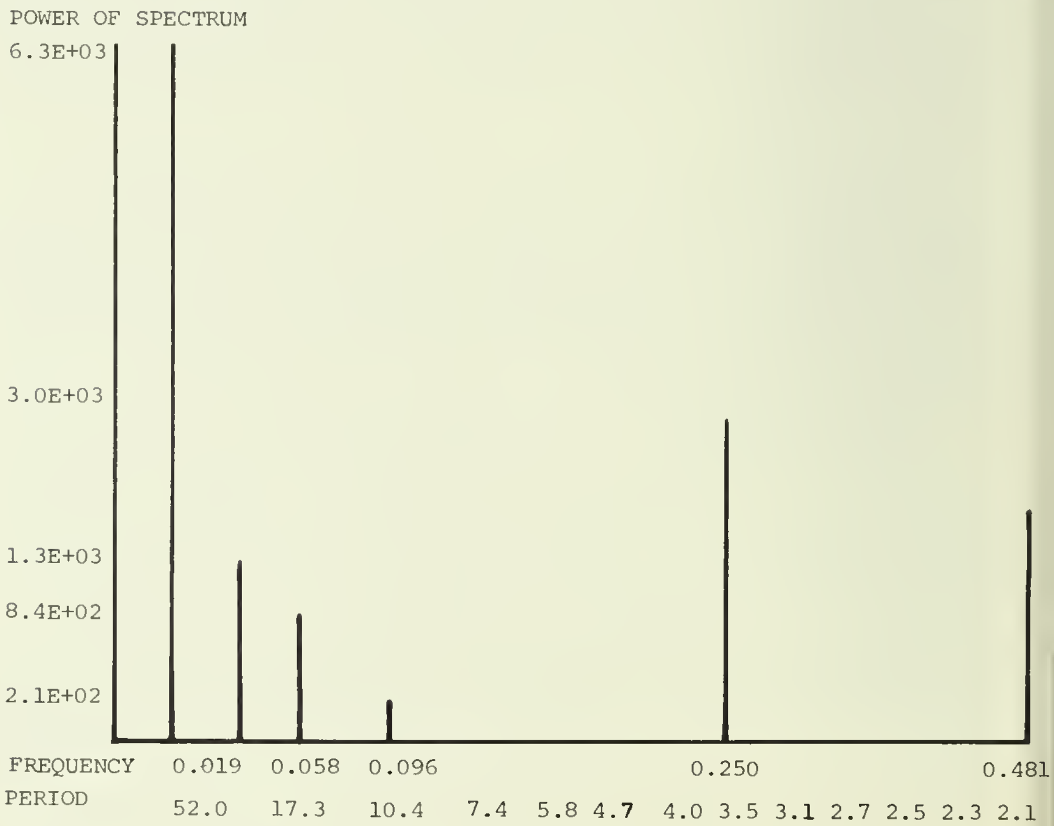


Figure 2.6. Periodogram of time series figure 2.5



DYNAMIC AND STATIC MODELS

Corporate models represent the time dependent activities of a firm. Since the model equations either depend explicitly on time, like in the trend model eq. (2.4), or relate state variables that refer to different time periods, like eqs. (2.1-2.5), corporate models are, in general, dynamic models. Such models are run and evaluated over a time horizon or planning period. Starting at a specified initial state, the state variables develop until the final state. Analogous to the terms used in the engineering and management sciences, the states a model or a system possesses at different stages or time may be classified as either transient or stationary. A model or system is said to be in a stationary state if the value of its variables do not change from period to period. The stationary state is called stable provided that the system returns to that state regardless of any changes in the values of the state variables.[3] It is characteristic for a great variety of systems that the stationary state is only reached after an infinite number of transient states.

The endogenous marketing model

(2.9) $$S_t = S_{t-1} + b \cdot S_{t-1} (S_\infty - S_{t-1}), \; b>0, \; t=[1,n]$$

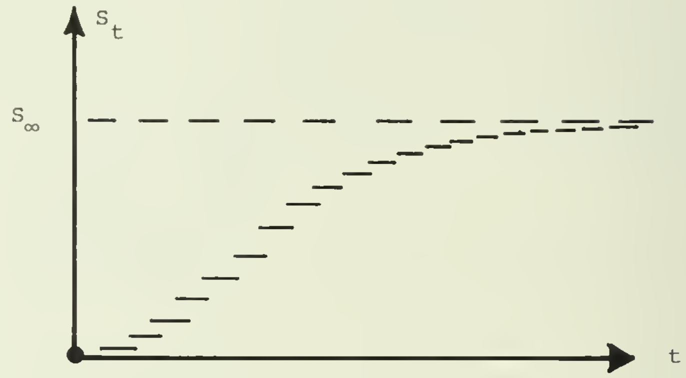
may serve as an illustration for the definitions that have been introduced above. It is assumed in the model that the difference $(S_t - S_{t-1})$ in market share of a product in two successive periods is directly proportional to the product of the market share of the first period, the difference between the maximum attainable market share S_∞ and the market share of the first period S_{t-1} and a proportionality constant b. Figure 2.7 shows a solution of the difference equation (2.9) for $S_0 > 0$.

The logistic model expressed by eq. (2.9) was first used by Pearl for population forecasts [115]. More recently, the model has been used with varying degrees of success in mid- to long-term demand forecasting for certain commodities [viz. 88, 96]. In most cases, the logistic hypothesis has been expressed in continuous models.

Figure 2.7 shows how the endogenous state variable S_t approaches its stationary value S_∞ after an infinite number of transient states. It should be realized, however, that the solution shown is a special one,

since the non-linear difference equation (2.9) also possesses oscillatory and exploding solutions for certain combinations of S_0, S_∞ and b.

Figure 2.7. Discrete logistic model



It is important to note in this context that the classical theory of the firm is a theory that essentially relates different stationary (static) states of a model. With respect to a short time horizon, this would be equivalent to the assumption that entrepreneurs have complete information regarding the markets and the internal structure of the firm and are able to react to changes in their environment with infinite speed. This implies that the economic system approaches a stationary state for different values of exogenous and decision variables in infinitely short time intervals.

Although the dynamics of most of the corporate models known today does not seem to be very complicated, models tend more to a description and comparison of transient states. State changes are assumed to occur not instantaneously, but in well defined time intervals within a finite time horizon.

STOCHASTIC AND DETERMINISTIC MODELS

So far, the discussion concentrated entirely on deterministic models, i.e. models for which the parameters, variables and structures were known with absolute certainty. The majority of corporate models that are implemented today are without doubt deterministic. Although probably most model builders would concede that this does not in all circumstances give a realistic picture of the situation of a firm, they seem to believe that the deterministic "What if?" questions described in chapter 1 allow a quantification of uncertainty and risk in model structure, variables and parameters. However, there are several reasons that may often speak against this assumption. One could not take explicit account of risk, because the answers to deterministic "What if?" questions do not indicate how different answers should be weighted. Furthermore, sensitivity analysis would in some cases lead to fallacious results due to the fact that one could not take into account all the interaction effects of variables and parameters. A number of authors, notable Howrey and Kelejian [77, 123], have shown that, except for linear systems, model results derived with deterministic parameters will in general differ from expected results derived from a stochastic model. The differences are possibly not very serious in connection with a basically linear and deterministic bookkeeping or financial model, but should be investigated more carefully at least for the marketing segment of a corporate model that contains non-linearities.

There are three main reasons why a deterministic model might not give a realistic picture of the firm: first, variables, parameters and the structure of a model may be stochastic by nature, secondly, the model equations may contain so-called equation errors, third, the measurements of the variables to which a model is fitted, may contain measurement errors

The first case may be illustrated by Figure 2.3. If a constant "number of orders per time unit" were used in a model, one would not be taking into account that a possibly stochastic process generates successive values of this variable. A deterministic model may lead to either optimistic or pessimistic results, because the distribution properties of the variable have been excluded from all considerations.

Equation errors in a model may either results from omitted variables in an equation, an inaccurate functional specification or incorrect use [103, pp. 6-13] of the equation. Equation errors may be committed on purpose, e.g. if variables are thought to have only a very small influence or if an inaccurate but simple, especially linear, functional form is thought to be a good approximation to the correct functional form. This choice then considerably reduces the effort required to estimate and solve a model. Other equation errors are only to a small extent under the control of the model builder: many variables of the firm are difficult to quantify. Expectations, tastes and attributes of the firm's employees or its customers influence its performance and sales [32]. The collection of primary data on these variables, e.g. by surveys, may give indications, but is rarely done because of cost reasons. Sometimes approximate dummy or proxy variables are used. In most cases, such variables are excluded from the models, because they are not known.

Measurement errors are either generated by the measurement process itself, i.e. the process by which data are collected, filtered, aggregated or disaggregated, or may be due to the sample properties of the data.

The above discussion leads to a stochastic and discrete generalization of the model equations originally expressed by eq. (2.2)

$$(2.10) \qquad \underline{f}_t(\underline{Y}_t, \underline{Y}_{t-1}, \underline{X}_t, \underline{\theta}_t, \underline{U}_t) = \underline{0} \;; \quad t = [1,n]$$

The model consists of a m-component vector equation $f_t = \underline{0}$ that is made up of algebraic and difference equations. The equations may contain exogenous and predetermined variables as well as endogenous and decision variables. Furthermore, $\underline{f}_t$ depends on a m-component vector $\underline{U}'_t = [u_{1t} \; u_{2t} \; \ldots \; u_{mt}]$ of stochastic disturbances.

PRACTICAL CONSEQUENCES

The surveys discussed in chapter 1 indicate that so far only a few corporate models take stochastic disturbances as introduced in eq. (2.10) explicitly into consideration. If one discusses possible explanations for this observation, one is obliged to make several distinctions. First, stochastic disturbances may be treated differently in alternative modeling steps. Second, the information model builders and users possess

about these disturbances determines how they employ them.

In the case that historical values of all variables in eq. (2.10) except the $\underline{U}_t$ are available, one may use a statistical estimation technique, e.g. multiple regression, to determine the model parameters. Such a technique usually supplies the parameter estimates together with a confidence limit. The $\underline{U}_t$ are obtained as residuals, e.g. as the scatter in the endogenous variables Y_t which cannot be explained by the model specified. If the estimated model is solved for the $\underline{Y}_t$ over the planning horizon, these $\underline{U}_t$ may be neglected and the solution would be called a deterministic solution or simulation. Alternatively, one might use the $\underline{U}_t$ generated in the estimation step to derive some properties of these disturbances. If they are reproduced and considered in a model solution, one deals with a stochastic simulation.

It is seen from eq. (2.10) that a deterministic solution or simulation will normally yield only one value for the $\underline{Y}_t$ for every t. On the contrary, different realizations of the $\underline{U}_t$ in a stochastic simulation will normally yield different values for the $\underline{Y}_t$. Several simulations are therefore necessary if one wants to calculate expected values or variances for the $\underline{Y}_t$.

The surveys indicate that the $\underline{U}_t$ are more often either implicitly or explicitly taken into consideration in the estimation step than in the solution step. Expected model parameters are then used in a deterministic solution. It is well known that a stochastic simulation for a linear model will not yield additional information about the behavior of the system described than is already available from the estimation. A deterministic simulation will for these cases also be a mathematically correct approach.

The available model descriptions indicate, however, that deterministic simulations are also used with models which are non-linear in the variables. Several explanations may be given for this observation.

A stochastic simulation always requires several model solutions which have to be paid for. The benefits obtained from it may approximately be quantified for models which have been estimated statistically: the correct stochastic solution differs from the deterministic solution and forecast.

The above conclusion only holds if the correct model and the objective distribution of the disturbances $\underline{U}_t$ are known. The literature and

also the discussion in chapter 1 indicate that this assumption is practically never fulfilled. Subjective judgements and estimates play an important role with practically every corporate model.

In a state of risk model builders and users are able to subjectively estimate the distribution of the $\underline{U}_t$. In states of quantitative uncertainty they are not able to assess distributions or probabilities. If they model and plan under structural uncertainty, they are not even able to discriminate between alternative model structures. Very often, corporate modelers are in one of these situations. The wrong subjective estimation of a probability distribution or model structure may then invalidate the results of a costly stochastic simulation. The sometimes intuitive understanding of these problems explains the preference model users have for deterministic models and solutions.

ANALYTICAL AND NUMERICAL SOLUTIONS (SIMULATIONS)

A survey of the literature on corporate models reveals that practically all models fit into the framework underlying eq. (2.10). If the structure of a "typical" corporate model is thus established, immediately the question arises how the model should be evaluated for practical applications. The discussion of the question is rather difficult for eq. (2.10), since it represents a system of possibly non-linear difference equations with changing structure

For a great number of applications, eq. (2.10) may be simplified to give the general linear model with constant coefficients.

$$(2.11) \qquad A\underline{X}_t + B\underline{Y}_t + B_1\,\underline{Y}_{t-1} + C.\underline{\theta}_t + \underline{D} = \underline{U}_t \;;\; t = [1,n]$$

in eq. (2.11) $\underline{X}_t$ would represent a (ℓ x 1) vector of exogenous variables, $\underline{Y}_t$ and $\underline{Y}_{t-1}$ (k x 1) vectors of endogenous and predetermined variables, $\underline{\theta}_t$ a (h x 1) vector of decision variables, $\underline{D}$ and $\underline{U}_t$ (m x 1) vectors of constants and stochastic error terms; A, B, B_1 and C are appropriate coefficient matrices of dimensions (m x ℓ), (m x k), (m x k), and (m x h), respectively. Equations (2.10) or (2.11) do not incorporate any inequalities or logical relations as may be important for practical applications whenever not only quantitative policies are investigated by determining

values for the decision variables, but also qualitative policies effect changes in the model structure (Tinbergen [139, p.3]). It will, however, be shown in a later chapter that such relations also fit into the conceptual framework as it has been outlined so far. Inequalities may be transformed into equations by either introducing nonnegativity constraints for some variables or some additional non-linear model equations. Binary (0,1)-variables may be employed to represent logical switches.

TYPES OF SOLUTIONS

It is easily seen that the endogenous variables $\underline{Y}_t$ for a "What if?" investigation are uniquely defined by

$$\underline{Y}_t = B^{-1} (\underline{U}_t - A\underline{X}_t - B_1 . \underline{Y}_{t-1} - C.\underline{\theta}_t - \underline{D}) \quad , \tag{2.12}$$

if $k = m$ and the inverse of B, B^{-1} exists. For $k < m$ the system is normally overdetermined, for $k > m$ it would normally be undetermined. In both cases, an additional objective function is required for an evaluation. In the first case, it quantifies the disadvantages connected with deviations from an exact equality, in the second case, it measures the trade-off between different solutions of eq. (2.12). The same observations hold for a "no external decision" evaluation which is characterized by $\underline{\theta}_t = 0$ and $\underline{U}_t = 0$.

Eq. (2.12) would be solved for the decision variables $\underline{\theta}_t$ if a target approach is chosen. Target values $\underline{Y}_t$ should be available and C^{-1} must exist for such evaluations. Again, the special cases of under- and overdetermined solutions may occur, notably if not all target values are supplied. As discussed above, an objective function must be available to evaluate these cases.

ANALYTICAL SOLUTIONS

Certainly the ideal solution to any model would be its analytical solution. If it existed, the endogenous or output variables $\underline{Y}_t$ of the model could explicitly be expressed by

(2.13) $\underline{Y}_t = \underline{G}_t \, (\underline{Y}_0, \underline{X}_t, \underline{\theta}_t, \underline{U}_t) \qquad t = [1,n].$

The analytical solution would be the ideal solution, because the model builder or decision maker could directly calculate the model output from given values of the exogenous variables, initial values of the endogenous variables and the disturbances, once he has specified the policies that he is interested in. It would not be necessary to solve or simulate the model for various times and parameter values. Instead, the answers to all the three types of questions that were identified in the preceeding chapter could be given directly by an evaluation of the analytical expression eq. (2.13). In many cases, the only calculation effort would consist of a substitution of known parameters, variables and disturbances. For deterministic linear models these calculations could often be effected by hand or with a desk calculator.

Thus, an analytical solution would have definite advantages over any numerical solution or simulation. An extreme opinion on this point has been expressed by Dorfman who states:

"The result of a simulation is always the answer to a specific numerical problem without any insight into why that is the answer or how the answer would be influenced by a change in any of the data [44, p. 604]."

Two simple examples can illustrate these points. They are special cases of the linear model with constant coefficients expressed by eq. (2.11). It is well known that this model possesses an analytical solution provided that the matrix B is a non-singular m x m square matrix (viz. e.g. [59]). But the examples are easier to understand if they are directly based on simplified versions of (2.11) instead of the general solution.

FORECASTING MODEL

Consider the single equation first order autoregressive forecasting model

(2.14) $y_t = (1 + \alpha) \, y_{t-1} + u_t \, , \quad t = [1,n] \, ,$

where y_t represents sales at time t, the parameter denotes a sales growth rate and u_t corresponds to a stochastic disturbance term.

Its analytical solution becomes

(2.15) $$y_t = y_0 (1+\alpha)^t + \sum_{j=1}^{t} (1+\alpha)^{t-j} \cdot u_j \quad , \; t = [1,n]$$

where y_0 is the initial value of y_t. A comparison of eqs. (2.14) (2.11) reveals that $h = \ell = 0$, $m = k = 1$, $\underline{D} = (0)$, $B = (1)$ and $B_1 = (-(1+\alpha))$. The solution eq. (2.15) allows directly a discussion of the dependence of sales y_t on its initial value, the sales growth rate, the time horizon of the model and the distribution properties of the disturbances u_t. In a simulation, the moments (e.g. expectations, variances, etc.) of y_t would be determined empirically from a number of recorded time paths of y_t. These would be generated according to eq. (2.14) using a suitable random number generator to sample values of the disturbances u_t (e.g. [106 and ref,]). Apart from the fact that the calculation effort would certainly be higher than for the analytical solution, one could not prove by simulation experiments that finite moments of the distribution of the y_t existed at all. (See Basman for an example [12]). This means that for certain models, it is possible to show analytically that simulation experiments would not lead to any results.

Via eq. (2.15) all three types of questions can be answered that have been discussed in the preceeding chapter. Since it does not contain any decision variables, the y_t would be answers to questions regarding the non-controllable environment of the firm. In the case that α could be considered as a decision variable, the answers to "What if?" or "What to do to achieve?" questions would, in most cases, immediately follow from eq. (2.15). If one assumes, for example, that the u_t have zero expectation and the expectation of y_t was a target value, it follows immediately that α should be

(2.16) $$\alpha = \left(\frac{y_t}{y_0}\right)^{\frac{1}{t}} - 1 \quad .$$

FINANCIAL MODEL

Consider the linear cost equation

(2.17) $$\underline{Y}_t = C \cdot \underline{P}_t \quad , \quad t = [1,n] ,$$

in which the vector $\underline{Y}_t$ denotes the unit costs of the products of the firm. The matrix C could be interpreted as a Walrasian matrix [42]. Its elements

c_{ij} would describe the quality of microeconomic factor i (e.g. labor, energy, raw materials) with factor price p_{it} needed to produce one unit of product j. The data from the right hand side of eq. (2.17) could be taken from the firms accounting system [73, 98]. Eq. (2.18)

$$\text{(2.18)} \qquad \Delta \underline{Y}_t = C \begin{pmatrix} p_{1t} \\ p_{kt+\Delta p_{kt}} \\ p_{ht} \end{pmatrix} - C \cdot \underline{P}_t \, ,$$

or

$$\Delta \underline{Y}_t = \underline{C}.k \quad . \, \Delta p_{kt}$$

would be the analytical answer to a "What if?" question regarding cost changes due to changes in factor price p_{kt} ; $\underline{C}._k$ would denote the column vector number k contained in matrix C. Alternatively, one might be interested in the factor prices p_{kt} in planning period t needed to stay below a certain cost y_{jt} of product number j. The answer would directly follow from

$$\text{(2.19)} \qquad p_{kt} \leq \frac{1}{c_{jk}} \left(y_{jt} - \sum_{\substack{i=1 \\ i \neq k}}^{h} c_{jk} \cdot p_{jt} \right)$$

Unfortunately, analytical solutions are only of minor importance in practical corporate modeling work and in most cases numerical analysis, especially simulation, is used to determine the output variables of the model. The main reason seems to be the complexity of the models which is a result either of the functional form or great number of the model equations. The terminology of multi-stage decision processes given in the preceeding chapter facilitates a classification of the model and its time dependent behavior. However, an analytical solution or even an optimal analytical solution of the model with respect to some objective function of the total firm using the currently available optimization techniques for multi-stage systems can only rarely be attained because of a number of quite specific reasons:

1) Even if the model may be represented by eq. (2.11), i.e. by a system of linear algebraic or difference equations with or without stochastic disturbances, the model is usually not solved analytically, but

numerically. Since the system characteristically consists of many equations ($m > 10$) the substitutions to be carried out with a completely recursive system, the matrix inversion required for a simultaneous system, and the determination of the characteristic roots for a system of simultaneous difference equations in general cannot be effected analytically in closed form. Furthermore, an analytical solution is of interest only if matrix B in eq. (2.11) is a non-singular ($m \times m$) matrix. Since one may deal with underdetermined systems of equations, especially in the production segment of a corporate model, linear or goal programming or variational methods may become involved. For an application of these methods necessary conditions for the optimum solution can often be formulated analytically, but the solution itself is effected numerically using a variety of different algorithms.

2) The system of equations may contain non-linearities in the state variables, the decision variables and the disturbances. Thus, the system in general cannot even be reduced to a linear algebraic system if one uses integral or summation transforms as are used for many engineering problems. Furthermore, the model may contain logical relationships that effect a change of the model structure at different times or if certain conditions are met. For underdetermined systems, the situation may be too complex for even a numerical solution by mathematical programming methods. Simulation could be the only available method of treating such situations numerically.

3) The parameters and the structure of a model may be very inaccurate, either because they have been estimated from non-experimental data or because they have been supplied subjectively. It might be doubtful if a carefully derived analytical solution would have more value than even a "quick and dirty" simulation (viz. Kruse [86]).

4) Neither from the microeconomic literature, not from descriptions of the corporate modeling work carried out thus far, can one derive much about overall goals and objectives of a real world firm.

It seems as if in most cases the objectives and goals of a firm were not fixed within a model, but that their formulation was rather left to the model users and decision makers with their subjective preferences. Under these circumstances, the value of analytical solutions is very doubtful.

5) To a certain extent, one may draw similar conclusions with respect to the available optimization techniques such as mathematical

or dynamic programming techniques. The number of stages, possible states and decisions per stage of a corporate model are often too large to allow an enumeration of feasible solutions for optimization. This restriction will perhaps become less severe in the future, when computers with a greatly extended storage will be available to business firms.

The application of optimization methods in corporate modeling is further limited because most techniques are very problem-oriented or tailored to deal with specific problems only. They are mostly not general enough to allow the fast evaluations or optimization of a model with non-linearities, logical switches and a changing objective function.

6) It is easy to imagine situations in which a model is solved numerically although it possesses an analytical solution. This might be the case if nobody in a corporate modeling team knew how to solve the model analytically or if it is possible to judge by experience that the search for an analytical solution would be extremely time consuming [130, 35]. One may again turn to numerical evaluation and especially to simulation. This point has especially been stressed by Cohen:

"People need not be powerful mathematicians in order to build and run computer models. It requires a much more extensive knowledge of mathematics to obtain an analytical solution to a complex mathematical model than it does to formulate the model. When simulation techniques are used, however, once the model is set up, the rest is relatively easy." [35, pp. 535-536].

MODELS FOR THE FINANCIAL, PRODUCTION AND MARKETING SEGMENTS OF THE FIRM

It was mentioned previously that most corporate models described in the literature have concentrated on the financial sector of the firm. These models have been used mainly for short- to middle-range financial modeling on a yearly time basis. Corporate models in which behavioral and organizational aspects of a firm's activities have been described do not seem to have found a widespread industrial application.

Structural equations for such a model are by no means easy to develop. Furthermore, the danger is great that on the one hand the variables and parameters used do not have an apparent meaning to the model users, on the other, that data and measurements are not available from the firm's information system to calculate, estimate and verify such models. Corporate financial models, on the contrary, are based on the

firm's accounting, budgeting and planning information and concentrate on the generation of financial statements that are of immediate value to the user. Today a great number of corporate planning and simulation languages are available that aid expecially in the construction of corporate financial models. They are discussed more thoroughly in chapter 8.

FINANCIAL MODELS

Figures 2.8 and 2.9 are examples of the kind of output a user of a corporate financial model usually obtains. The two figures constitute the basic solution to a financial model that is discussed in chapter 7 mainly for expository purposes. Figure 2.8 shows the balance sheet and Figure 2.9 the income statement of a CIBA-GEIGY subsidiary company over a time horizon of 8 years. The model shows the time dependent behavior and development of approximately 40 variables. About half of the variables are defined as totals (e.g. "Total Current Assets") or differences (e.g. "Divisions Total Contribution" is equal to the difference between "Total Sales" and "Division Expenses" and "Total Local Cost of Goods Sold"). Of the remaining variables again about half may be termed as stock variables, the others correspond to flow variables. The first group of variables are contained in the balance sheet, whereas, the second group of variables appear in the profit and loss statement of the firm. Both groups are interrelated according to the duality principle of accounting (viz. Mattesich [98, pp. 26-51]). Changes in the firm's variables are recorded and described in two different ways. In the balance sheet, the new value of a variable is calculated from its final value in the previous period plus increments minus decrements. In the profit and loss statement, the same increments and decrements are aggregated to generate income and expenses in one single time period. The difference between the latter is transferred to the balance sheet to either directly show losses or profits or, in Figure 2.8, effect changes in the stock variable "Retained Earnings."

In case all the increments and decrements of a corporate financial model are determined outside the model, it attains a very special structure with respect to the general linear model expressed by eq. (2.9). Stock variables which are not defined as totals are described by deterministic (e.g. $\underline{U}_t = 0$) first order (p = 1) difference equations. If one

Figure 2.8. Corporate Financial Model Balance without Investment and Optimization

BALANCE SHEET — Company Australia

5-Year-Plan 1977 to 1981

Conversion rate into SFR.	4.80	4.80	4.80	4.80	4.80	4.80	4.80	4.80
				Plan				
	1974	1975	1976	1977	1978	1979	1980	1981
Assets								
Liquid Funds								
Receivables	1292	1694	2101	2606	3232	4008	4971	6166
Inventories	4684	5429	7135	9308	11481	13654	15827	18000
Other Current Assets	100	100	150	150	150	150	150	150
Total Current Assets	6076	7223	9386	12064	14863	17812	20948	24316
Fixed Assets	975	960	1273	1483	1728	2013	2345	2732
Other Fixed Assets	2	2	2	2	2	2	2	2
Total Long Term Assets	977	962	1275	1485	1730	2015	2347	2734
Total Assets	7053	8185	10661	13549	16593	19827	23296	27050
Liabilities								
Banks	2012	2324	2244	2167	2092	2020	1951	1883
Current Account Parent Company	1800	2000	2300	2645	3042	3498	4023	4626
Other Short Term Liabilities	600	740	890	1070	1287	1548	1862	2240
Total Current Liabilities	4412	5064	5434	5882	6421	7066	7835	8749
Parent Company Loans	729	729	729	729	729	729	729	729
Banks & Other Financial Establishments	1862	1862	1862	1862	1862	1862	1862	1862
Other Long Term Liabilities	863	963	963	963	963	963	963	963
Total Long Term Liabilities	3454	3554	3554	3554	3554	3554	3554	3554
Share Capital	2000	3000	3500	4800	6100	7400	8700	10000
Reserves	134	134	134	134	134	134	134	134
Retained Earnings	-2947	-3567	-1961	-821	383	1673	3072	4613
Total Liabilities	7053	8185	10661	13549	16593	19827	23296	27050
Local Profit After Taxes	1742	-620	1606	1140	1205	1289	1399	1541

Figure 2.9. Corporate Financial Model Profit and Loss Statement without Investment and Optimization

PROFIT AND LOSS STATEMENT — Company Australia

5-Year-Plan 1977 to 1981

Conversion rate into SFR.	4.80	4.80	4.80	4.80	4.80	4.80	4.80	4.80
	1974	1975	1976	Plan 1977	1978	1979	1980	1981
Sales								
- Third Parties	10374	12670	14604	17519	21015	25210	30242	36278
- Intercompany								
Total Sales - Local Currency	10374	12670	14604	17519	21015	25210	30242	36278
- SFR	49795	60816	70099	84090	100874	121008	145106	174133
Division Expenses	1185	1633	2106	3497	5807	9642	16010	26584
Total Local Cost of Goods Sold	7579	8434	10705	13588	17247	21891	27786	35268
Division Local Contributions	1610	2603	1793	434	-2038	-6323	-13554	-25575
Function Expenses								
.	638	705	780	863	955	1056	1169	1293
Personnel	74	91	195	418	895	1919	4112	8810
Managerial	169	165	190	205	220	237	256	276
Loss on Revalaction								
Other Income and Expenses								
Total Function Expenses	881	961	1165	1486	2071	3213	5536	10379
Local Contribution	729	1642	628	-1051	-4109	-9535	-19090	-35954
- Expenses	350	370	375	380	385	390	396	401
- Income	1363	-1892	1353	2571	5699	11215	20885	37896
Income from Minority Interests								
Local Profit before Taxes	1742	-620	1606	1140	1205	1289	1399	1541
Taxes								
Local Profit After Taxes	1742	-620	1606	1140	1205	1289	1399	1541
Payments to Minority Share Holders								
Local CIBA-GEIGY Net Profit	1742	-620	1606	1140	1205	1289	1399	1541

excludes all totals from the discussion, then the stock variables may be grouped in such a way that the matrices B and B_1 become diagonal matrices (viz. Tinbergen [139, p.31]). The monetary values of the flow variables of the income statement may be calculated from linear and independent algebraic equations with unit coefficients. A model with such an extremely simple mathematical structure should perhaps best be called a "budget or plans generator." It can give answers to all three types of questions which have previously been identified.

The computer with this type of model is mainly used as a fast adding machine. But a numeric solution thus generated can save many man-weeks of manual bookkeeping and plan-consolidating, especially if corporate simulation and planning languages are used to code the model structure. The answers to "What if?" or "What to do to achieve?" questions can be given analytically for deterministic as well as stochastic models without many difficulties, if in the latter case, for instance, the normality of the disturbances is assumed. In practice, this is not done, because all the necessary substitutions and calculations are effected much faster and with fewer numerical errors on a computer. A numeric solution becomes even more important if the "budget generator" made up of decoupled linear equations is extended to incorporate recursive or simultaneous systems of equations. It is thus possible to take into account the simultaneity and non-linearities, as well as more complicated stochastic disturbances, in some model equations not only in the financial, but also in the production and marketing segments.

FINANCE, MARKETING AND PRODUCTION MODEL

The above observation may be understood from Figures 2.10 to 2.12 which show the model structure and a computer output for a corporate model that describes purchases of raw products, production in two stages, inventories, sales and finance of a hypothetical three product firm [89,122].

The computer output exhibits the value of the financial variable "Liquid Funds" as a function of time and an exogenous marketing variable "Demand for End Product Number Three." The regular time pattern of this variable was not observed in reality, but was generated to test the stability of the whole model at various frequencies.

In Figures 2.10 and 2.11, the flows of materials or products,

Figure 2.10. SIMSYS representation of corporate models. Material, information and personnel flow.

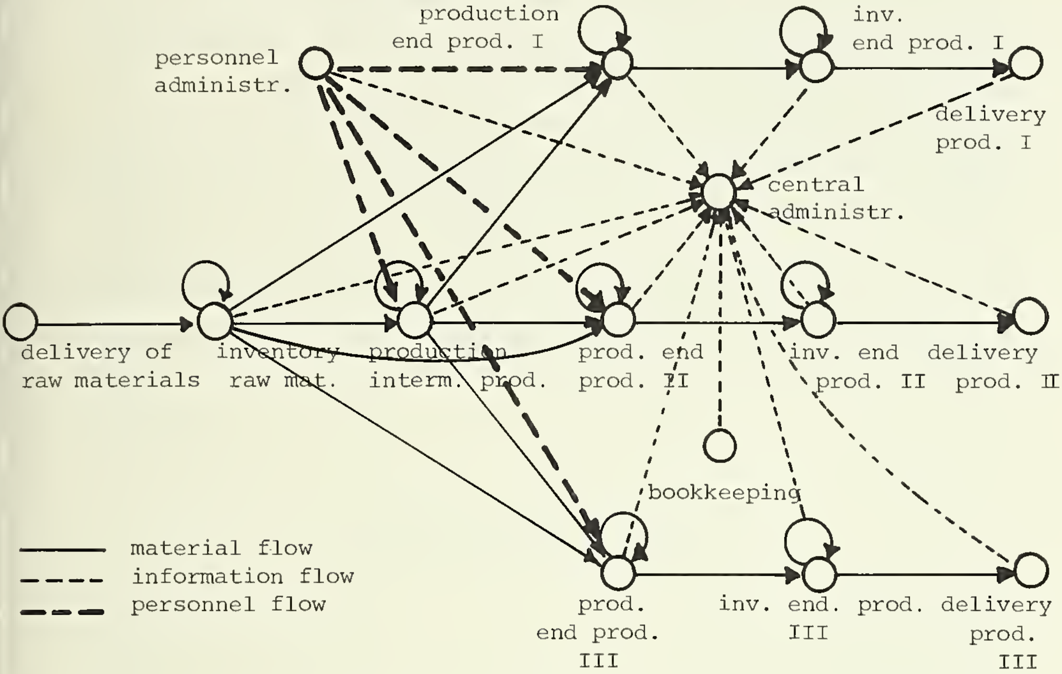
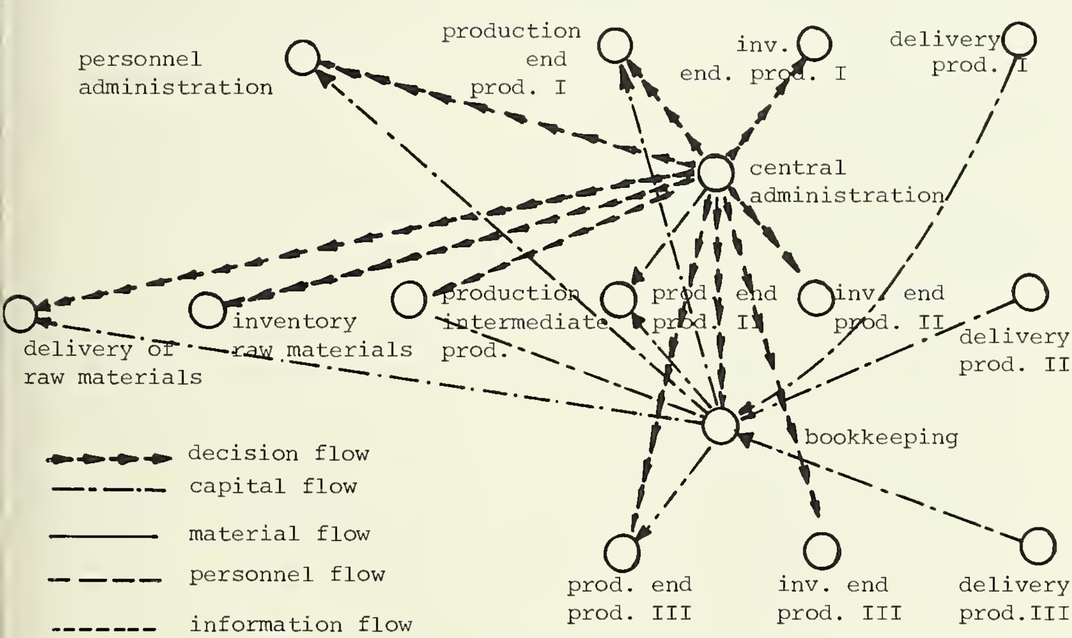


Figure 2.11. SIMSYS representation of corporate models. Decision and capital flow.



capital, personnel, information and decisions within the model are represented by SIMSYS-graphs (Simulation of Systems) as they have first been used by Kaufmann [81]. For a more explicit description, see Berthillier and Frely [18]. Similarly to Forrester [51, pp. 68-69], Kaufmann distinguished in his dynamic models between so-called "modules" [18, p.47], or "levels" and flows between modules. The first are represented by the nodes, the latter by the arcs of the graph. One can say that, in the accounting sense, stock variables are defined on the nodes, flow variables on the arcs of the graph. The stock variables describe the population of a level or module in which flows are accumulated or transformed and it is assumed that level variables can only be controlled via decisions on inflows and outflows. For example, one sees from Figure 2.10 that the inventory level for raw products at a certain time is calculated from its value in the previous period (self-loop) plus new deliveries between the two periods minus deliveries to the production stage for intermediate products. The inventory level is supplied to the inventory administration which sets the values of decision variables describing inflows and outflows of the level.

There is a certain correspondence between SIMSYS-graphs and signal flow-graphs as have been used for a very long time especially by electrical engineers to represent systems of linear algebraic or difference and differential equations (viz. Mason (97], Coates [34]. Economic applications have been described by Tustin [142], Elmaghraby [48], Ponsard [117] and Niedereicholz [113]).

Quite independently from such details, Figures 2.10 and 2.11 give an impression of how a graphical representation facilitates the understanding of a model structure for complex systems.

The model shown was primarily designed to test the effects of different modeling techniques on the dynamic behavior of the state variables (Lindenmayer [89], Rosenkranz [122]). It consisted of about 65 mostly higher order and non-linear difference equations, some 80 algebraic and non-elementary equations and some 80 identities. The model contained approximately 40 variables which were decision variables according to the definitions that have been given earlier. Parameters and initial values of the predetermined variables of the model were assumed, not estimated. The insights gained from the experiments with the test model were used in a real world application in which the activities of a multi-product

industrial firm that produced electronic equipment were described (Lindenmayer [89]).

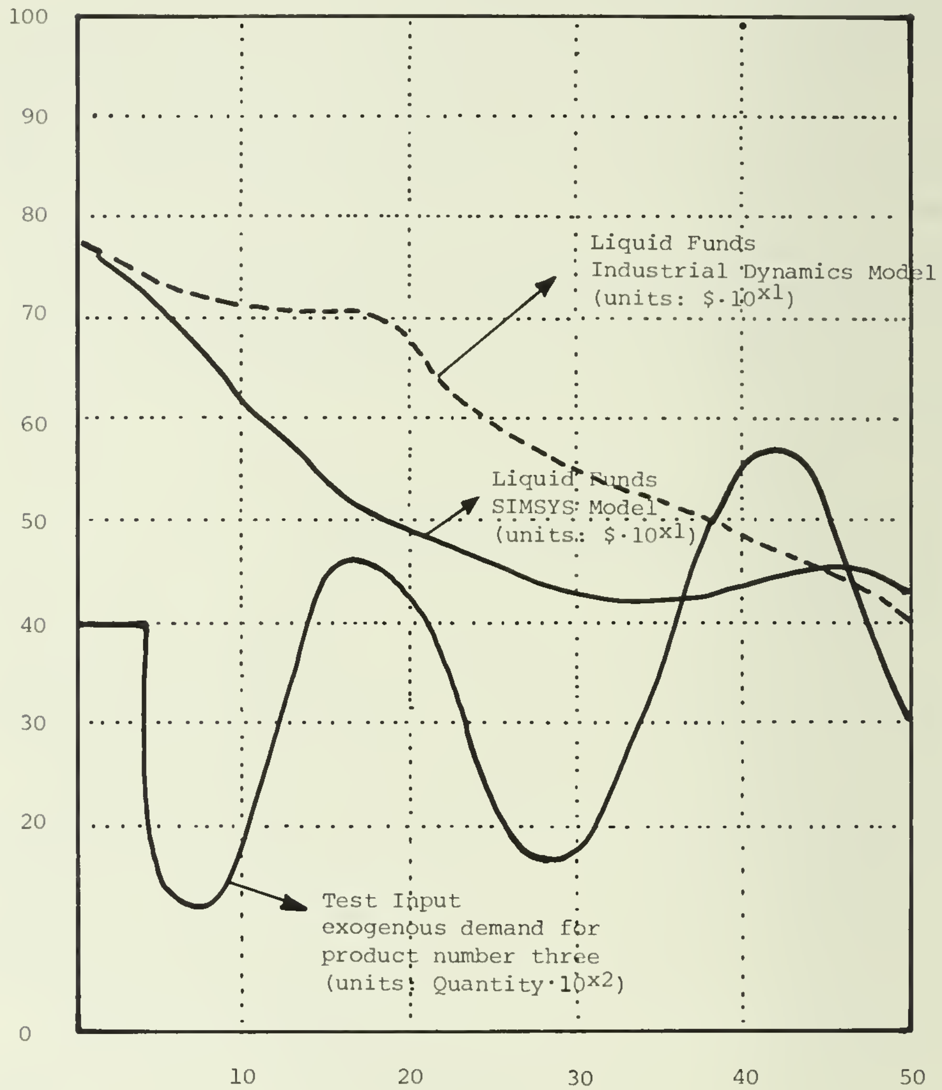
Compared to other models constructed within CIBA-GEIGY, but also in other firms, both the financial model and the corporate model shown in Figures 2.8 to 2.12 may still be considered small with respect to the number of equations and the amount of data used. In both cases, analytical solutions were not of practical interest. In the financial model, the large number of necessary substitutions would have been too large, in the second model it would have been highly questionable, if an analytical solution existed at all. So the models were solved numerically in both cases.

CONSTRUCTION AND USE: SOME PRACTICAL CONSIDERATIONS

Any project team inside or outside a company that either decides to or receives the mandate to develop a corporate model should be aware that its activities are only going to represent an attempt to model the firm. This indicates that the outcome of the modeling activities does not necessarily have to be either of practical relevance for a real world firm or supply new theoretical insights with models of fictitious firms.

Within CIBA-GEIGY, three models were abandoned after the construction had already reached quite a mature state. In all cases, approximately 2 man-years of analysis, data collection and computer coding had been invested. One of the models was a very large model that described in detail the operations of a multi-product subsidiary company in the area of production, with less detail in the areas of marketing and finance. The other two models concentrated on the description and simulation of the markets of two divisions, the sales of several hundred products to these markets and the flow of funds and marginal income connected with sales and distribution of the products on a worldwide basis. One of these models was abandoned before the construction of a production segment was begun. The marketing and financial segments had already been completed. The marketing and production segments of the other model were already implemented and used, but difficulties with the construction of the financial segment stopped all further modeling efforts.

Figure 2.12. Production, inventory and financial model, computer plot.



It seems as if such failures can be attributed to a number of often interrelated causes. Although the following chapters will mainly deal with the methodological side of corporate model building, one should be aware of the fact that the success of a corporate modeling project is often endangered by the modeling environment within the firm. The following pages will give a brief description of this environment together with risks and opportunities coming from it.

Failures seem in most cases to be attributable to the following four causes:

- Incompatibilities with a firm's organizational structure or its planning and controlling philosophy and procedure;
- Inappropriate project organization and management. This includes a host of unsolved communication, behavioral and educational problems;
- Insufficient or inadequate data processing support;
- Inadequate use of the available modeling methodology.

In the sequel these problem areas will be discussed in more detail.

CORPORATE MODELING AND THE PLANNING PROCESS

Several authors have defined planning as an intellectual anticipation and the design of a desired future and an analysis of the means of bringing this future about. Since experiments with a real firm are very costly or not feasible, a CSPM may be used as a tool to investigate alternative futures and managerial actions. Activities of a planning process may partially be formalized and supported by models and the computer. However, it should be realized that many activities are not programmable [46, 63]. The planning process and system as well as "mental planning models" make up the basis for formalized models. One of the main problems in corporate modeling is to define the border, interface and communication of mental planning activities and formalized models (viz. Keen [82]).

Both assumptions and data are frequently generated by the planning and controlling system and process of a firm. Such a planning system relies on its planning philosophy as well as technology and is adapted to it. It looks different for alternative organizational structures, but in the sense of a strategic management may include the planning of such a structure. A CSPM should be compatible with and integrated into the planning and controlling system and process. Both should use the same

definitions and hypotheses and serve the same ends. Otherwise, there is the danger of duplication of planning work or of the distortion of planning information.

Over the last 20 years, planning and controlling systems used in firms have undergcne several changes and others may be expected for the future. Several authors distinguish up to four types of planning. Most larger industrial firms so far have implemented two to three types of planning: liquidity oriented short-term planning and budgeting, profit and rentability oriented middle-range or tactical planning, profit potential oriented strategic planning [2,29,25,26,30,36,54,61,72,91,93,104]. Some firms have started to implement systems for survival and adaptability oriented strategic management (viz. Ansoff [7,8]). Care must be taken that a CSPM reflects and is able to adapt to a changing planning process and type of planning. Szyperski and Welters note that something like an interdisciplinary theory of the firm does not exist. Consequently, one may not expect a closed theory of planning, but a pragmatic philosophy and technology of planning [135, p.268]. These reflect the changes in the outer and inner environment of the firm and the state of the computer sciences.

Several authors (viz. Boulden [22, p. 237-240], Hayes and Nolan [71], Szyperski, et al. [136]) have distinguished different types of planning systems and processes. They will briefly be described in the following sections in order to discuss possibilities of model support.

Bottom Up

First generation or bottom up systems were used by many firms between the mid-fifties and mid-sixties. Based on a planning procedure defined in something like a planning manual, strategies and action programs were mainly formulated by the operational units of the firm. They were handed over to a company's central management without much involvement of the intermediate organizational units (viz. Figure 2.13). The operational units expressed their objectives, momentum as well as development strategies mainly in non-monetary units, like market share or volume of sales.

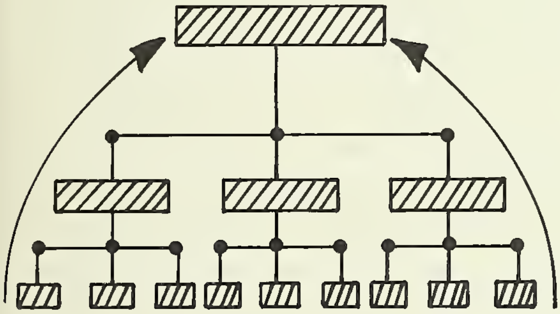
The central management decided on these proposals using mainly financially oriented financing, acquisition or divestment criteria and strategies.

These first generation planning systems and procedures derived from it had the advantage of generating planning information regularily in a fixed form and with unique definitions. Usually, they were very calendar oriented.

Their disadvantages were also easy to identify: with respect to the beginning external disturbances described in chapter 1 and the increasing complexity of the firms themselves, these systems were too slow, rigid and not very specific. The bottom up nature of the planning process with largely missing involvement of the intermediate functional or product oriented organizational units and their management caused distortions of planning information. The planning assumptions of the bottom and top units were based on different goals, objectives and value systems. There were not many institutionalized contacts and negotiations to close this gap (viz. Szyperski, et al. [136]).

First generation systems were supported by computer-based planning information systems which were mainly report and history oriented. Rigid file structures and commercial programming languages like COBOL and RPG were employed. Model support of the planning process was largely missing and took the form of data aggregations and consolidations or operational models, e.g. production planning models, for the operational units.

Figure 2.13. Bottom up planning process



Company
Top Management Level

e.g. Subsidiary Company Level

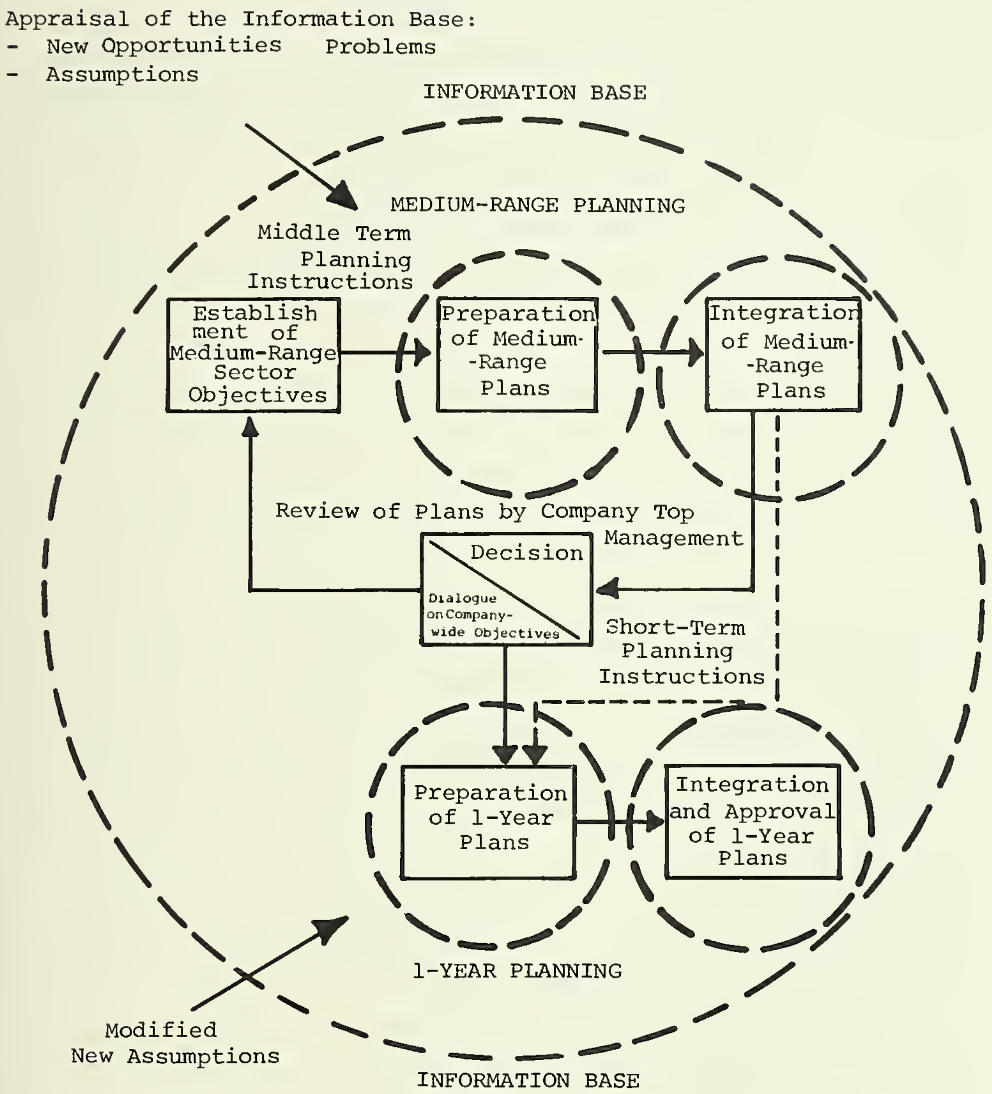
e.g. Operational Division
within Subsidiary Companies

Top Down

As a consequence of these shortcomings, companies started to introduce second generation or top down planning systems between the mid-sixties until the mid-seventies. Most of the planning procedures which are used today are of this second type. The bottom up reporting oriented procedure was complemented by a more specific top down procedure and planning activities as is indicated in Figure 2.14. Like the first generation systems, the planning process is carried out in a cycle defined by a planning procedure. The procedure allows the generation of a planning information base by calendar dates and defines rules to evaluate it. The planning cycle consists of several phases in which different planning activities are carried out by different organizational units and levels of aggregation.

On the top management level supported by staff functions,stylistic objectives and headquarter strategies (viz. Vancil and Lorange [143,91]) are formulated. They are based on an environmental analysis and an analysis of strengths and weaknesses with respect to functional, product and geographically oriented activities of the firm. A project oriented strategic planning process deals with particular business opportunities and dangers. The definition of business objectives, the environmental analysis and the stratetic planning process create an information base which is explained to the planning subsidiaries and divisions or functional groups (viz. Figure 2.14). Quantitative objectives like ROI, ROA, EPS, debt/equity ratios and productivity figures are defined and negotiated. Often the use of index performance ratios is institutionalized (viz. Staehle [134]), Reichmann, et al. [120]). This input is used by the divisions, subsidiaries and functional groups for a middle-term planning process which consists of decomposed planning activities. The result is fed back to the top by a stepwise bottom-up process. It is centrally aggregated and consolidated. The results are used as a basis for discussions and more accurate negotiations about middle-term financial, production and marketing objectives. The information and consensus thus generated is then fed into a short-term planning and budgeting process. It is carried out on the lower operational levels, but is again centrally consolidated and approved. Both the information generated by the middle-term and short-term planning process is employed for control purposes and to trigger corrective actions by upper organizational levels.

Figure 2.14. Planning steps of top down system



Compared to the first generation systems, the second generation approach possesses definite advantages: it is more problem and task oriented. Because of its feedback nature the assumptions, goals and objectives of adjacent organizational units are confronted with each other. Sikora notes that "... corporate planning may be conceived as a game for which the formalized planning procedure defines the rules [129, p. 284 author's translation]." The planning dialogue thus reduces the distortion of planning information, increases opportunities for participation and gives more responsibility and motivation to the planners at different levels. While the first generation systems were report oriented, second generation systems are more decision oriented. Several disadvantages connected with the use of second generation systems were identified more recently: they are often criticized for generating too detailed planning information at too high costs. Some critics argue that planners in different organizational units are absorbed too much by the collection of routine information as is needed for input to the middle range and short-range planning process (viz. Ansoff, et al. [8], Szyperski, et al. [136]). Since calendar deadlines have to be met, they often have not enough time to deal with planning problems met in the areas of strategic management and planning. The response to the previously described environmental changes and turbulences tends to be too slow.

It seems as if most corporate models known today support especially the middle-range and short-range planning activities (e.g. [127]). This conclusion is also supported by the survey results cited in chapter 1. The planning activities encircled in Figure 2.14 may be partially automated using a model. The reduction of clerical work thus achieved, the possibilities to calculate alternative plans and scenarios in a short time are a great progress and allow the approximate evaluation of alternative states of uncertainty and management decisions.

The development of CSPMs described above are not only a consequence of changes in planning philosophy and technology, but were decisively influenced by the development of computer hardware and software. Storage and processing costs have dramatically decreased. Planning file structures have become more flexible. The development of programming languages like PL/1 or special purpose planning software (viz. chapter 8) has made the use of more scientifically oriented planning tools and models possible and enabled planners and users to directly participate in the model building process.

Third Generation Systems

The disadvantages noted for second generation planning systems and processes have caused a number of firms to introduce several changes and extensions to the existing planning processes.

Such third generation systems still incorporate a middle-range and short-range planning process which contains the activities shown in Figure 2.14. They are still performed on a regular basis, but in contrast to first and second generation systems there is a tendency to decentralize, call for less detail and frequently adapt the formulation of plan requirements. As a consequence, the amount and type of planning information to be collected may vary strongly between different organizational units and from planning cycle to planning cycle.

The ideal of a third generation system is a continuously ongoing and adaptive planning process. The results of the middle-range and short-range planning process may be conceived as snapshots from this process. Planning units are expected to maintain permanently updated information bases. They do not only contain expected plans, but also optimistic, pessimistic and contingency plans.

The middle-range and short-range planning processes again obtain their input from an ad hoc and strategic planning process. This process tends to be irregular of varying content, and both project and task oriented. It incorporates an environment analysis, strategic management to plan the organizational adaption of the firm to a changing environment and typically, a business portfolio planning process (viz. Henderson [72], Hinterhuber [75]).

Planning teams for the strategic and ad hoc planning process have more often something like a matrix structure, instead of the strictly hierarchial compositions of functional or divisional planning teams observed for bottom-up and top-down processes. This tends to simultaneously involve planners who define and set objectives and targets, people who are responsible for their operational achievement and others who directly perform project work (viz. Ackoff [3]). The increased participation of several hierarchial, organizational and functional levels in the planning process is supposed to further decrease the distortion of planning information. Several companies discuss systems of financial incentives to be tied to performance measures in order to avoid the famous "hockey stick effect" of extrapolative planning. Others plan and introduce new

organizational structures. A company like Texas Instruments has institutionalized dual organizational structures. One structure is operation oriented as is shown in Figure 2.13, the other is planning oriented and e.g. distinguishes the levels of goal setting, objectives formulation, strategic and tactical planning [83]. One may expect the evolution of still other organizational structures.

The following requirements for model and computer support have to be fulfilled for a planning system as it has been described [19].

Computer Support of Third Generation Systems

CSPMs still support the regular bottom-up or top-down processes mainly in the planning activities which are encircled in Figure 2.14. Both models and the supporting corporate simulation and planning systems should fulfill the following requirements:

- The database and the model structures must possess different levels of aggregation and hierarchial structures which are a picture of the true operationally and planning oriented organizational structure.

- It should be possible to decentralize both the database and model structures. Users on different organizational levels should be enabled to use models they are authorized to employ for their planning.

- The models should supply an automatic interface between the models of different organizational levels. The structure of the model-interface should automate aggregations, disaggregations and consolidations.

- The supporting corporate simulation and planning system (CSPM) should incorporate the means to easily deal with large numbers of tabular data, e.g. balance sheets, profit and loss statements, financial key figures, sales and production reports. It should be possible be efficiently treat tree-structures of tabular data as would be used for organizational structures like in Figure 2.13.

- It should be easy to write model output in a form compatible with the reports used within the planning and controlling procedure.

Additional features must be provided to support the strategic and ad hoc planning process:

- It must be possible to quickly assemble, change and delete models that describe the aspects of a certain strategy, project or environmental scenario.

- The system must possess integration capabilities. It must be

possible to easily link models to environmental databases or to specify assumptions about the development of a company's environment. A user should also be able to combine the model based ad hoc planning process with the regular middle-range and short-range planning process in order to show an overall picture and the influence which certain projects or developments have on an organizational unit or the company as a whole.

- The system must be user oriented. Ad hoc planning teams will be composed of members from several organizational units and hierarchial levels. This calls for modeling systems which support users with different backgrounds, i.e. users not having a background in quantitative methods and data processing, but also modelers who want to do statistical analysis, forecasting or even resource allocation using management science techniques.

Like with first and second generation systems, the requirements formulated above are a result of the problems encountered with earlier planning systems in the present economic situation. They have also been influenced by the status and foreseeable developments of computer technology. Their achievement does not seem to be constrained by computer technology, but by the state of planning technology (viz. Lorange and Rockart [93, pp. 18-22], Syzperski, et al. [136, p. 453]).

The storage and processing costs connected with a model of any type will continue to decrease. The use of intelligent terminals, front-end computers and telecommunication networks allow both decentralized modeling activities and an integration of regionally developed CSPMs.

It has already been noted in chapter 1 that the demand for external information and macro-models has caused a number of private service bureaus to supply such services to business firms. The problem with these services is not their technical linkage to CSPMs, but the definition of an interface between internal and external models as well as between in-house and out-of-house modeling activities. Some firms construct their CSPMs out-of-house using one of the available communication and computer networks, others buy external information and forecasts on tape or use terminals to load such information directly into their in-house systems and CSPMs. Still other firms start to construct in-house strategic and competitive databases.

Especially, the strategic and ad hoc planning process calls for a support by on-line timesharing models and systems. Both systems or

packages and models are available in an increasing number from consultants, the computer manufacturers or by in-house development. Interactive programming languages like APL are in an increasing number also used by business firms. The types of database and database languages required are available today or may be expected in the near future.

While the technical support of third generation systems does not seem to be the constraining factor for further developments and implementation, the modeling side is likely to be more difficult. At the present state of the art it is not entirely clear how far the support of planning activities by formalized models and the computer may go. Figure 2.15 depicts a possible structure for computer-assisted planning activities (viz. Cohen [36], Lorange and Rockart [93]). It is clearly seen that CSPMs have the potential to support all types of planning indicated and be it only by simple database evaluations, even for strategic management purposes. However, problems in the tactical and operational area usually possess a simpler structure; planning activities are more often programmable and have a repetitive character. This explains the frequent use of models in these areas. Applications of ad hoc CSPMs in the strategic area should have a high yet largely unexploited potential.

ORGANIZATIONAL AND BEHAVIORAL ASPECTS

A number of surveys and reports indicate that CSPMs are often used on a rather high management level. Although there is no doubt that a large number of organizational and behavioral factors are responsible for the success or failure of a model, it is yet not possible to state the nature and relative importance of these factors. Since implementation research itself influences the type of model to be selected and the implementation strategy to be adopted, it will in this dynamic environment in addition always be difficult to make such statements.

Nevertheless, all surveys and reports agree that top management support is a very important organizational and also decisive behavioral factor. Among other factors this may explain the relatively high acceptance CSPMs have found compared to other types of management science models.

Figure 2.15. Planning activities and computer support

Planning Activity	Description	Computer and Model Support
STRATEGIC MANAGEMENT		
Planning Control	Formulation, adaption, decision on and control of general economy stylistic political/social environmental organizational goals. Survival, robustness, and flexibility goals.	Evaluation of strategic environmental competitive database [33,84,112]."What if?" analysis of alternative organizational structures
STRATEGIC AND AD HOC PLANNING		
Analysis of the environment	Verbal and quantitative description of the environment and different scenarios.	- database evaluations - "What is?", "What has been?" questions - use of econometric national, industry, business and raw material models.
Goal formulation	Largely qualitative formulation and negotation of economic goals	
Weighting of goals and setting of objectives	Negotiation about and formulation of quantitative goals, targets, and measures of performance. Decomposition of performance measures. Construction of index systems. Survival, long-range profitability, rentability and market potential objectives	- input-output models - business field classifications [72,75] - database evaluations - "What is?", "What has been?", "no external decision," "What if?" questions - "What to do to achieve?" questions lower organizational units using business middle-range models

Figure 2.15. (cont'd)

Planning Activity	Description	Computer and Model Support
Strategy Formulation	Formulation of financing, investment, divestment strategies by upper organizational levels. Definition of momentum, diversification strategies by operational organizational levels.	Storage of objectives in middle-range planning models Database evaluations Use of investment planning models. Sensitivities, risk [30,69], and experience effects [72,75].
Gap Analysis	Comparison between objectives and stragegy output [5,75].	Value input to middle-range planning models
Strategic Search and Selection	Search and selection of gap closing strategies mainly for investment and divestment strategies [30,69].	Portfolio analysis models "What if?" and "What to do to achieve?" analysis using middle-range planning models.
Implementation of Strategic Process	Decision of a set of strategies	
Strategywise Measurement, Feed-back and Control	Reordering of ongoing activities, triggering of corrective measures.	Storage of results and contingencie in databases Use of investment planning models "no external decision" questions middle-range models Comparison operations using middle-range business planning models
MIDDLE-RANGE PLANNING		
Setting of objectives	Formulation and decomposition of financial, marketing and production targets. Middle-range profitability and rentability objectives.	"What if?" analysis using middle-range planning models by upper organizational levels.

Figure 2.15. (cont'd)

Planning Activity	Description	Computer and Model Support
Preparation of Plans	Formulation of quantitative plans by the operational organizational units. Financial quantities, sometimes physical flows.	Database evaluation "What if?" and "What to do to achieve?" questions posed by operational units.
Integration and Consolidation	Establishment of a company-wide plan and contingencies from local and operational unit input	Use of macroeconomic databases and models to construct econometric marketing models, exposure management models
Dialogue and Decision	Comparison of plans and objectives, gap analysis with respect to momentum, diversification and financing strategies, decisions on gap closing activities.	Middle-range capacity planning, balancing and financing models Database evaluations
Implementation, Measurement and Control with respect to Organizational Units.	Recording of ongoing activities, triggering of corrective measures	"No external decision" analysis by upper organizational levels Database evaluations "What if?" and "What to do to achieve" questions by upper organizational levels and operational units. Storage of results in middle-range planning database Storage database "No external decision" questions middle-range planning models

Figure 2.15.(cont'd)

Planning Activity	Description	Computer and Model Support
SHORT RANGE PLANNING		
Setting of Objectives Preparation of Operational Plans	Formulation and decomposition of middle-range objectives. Quantity oriented: liquidity, sales, costs, marginal income	"What if?" analysis using short-range planning and budgeting models by management of operational units Database evaluations
	Formulation of short-range plans by the operational organizational units. Concentration on physical flows and financial figures.	"What if?" and "What to do to achieve?" questions posed by operational units Use of macroeconomic database and forecasts to construct marketing models cash management and hedging models
Integration, Consolidation and Approval	Establishment of a company-wide plan from local and operational unit input	Marketing-mix and operations oriented production planning models Database evaluations
Implementation, Measurement and Control	Recording of ongoing activities, triggering or corrective measures	"No external decisions" analysis by upper organizational levels "No external decision" questions short range planning and budgeting models

The survey undertaken by Grinyer and Wooller [64, p.17] indicates that corporate modeling project work is mainly carried out by operations researchers, accountants and financial analysts, as well as data processing personnel. Such team members are organizationally very often within the control and finance departments of a company and two to four organizational levels below the user or sponsor level.

As a result users and model builders tend to have different ages, educational backgrounds objectives and value systems. Hall notes that

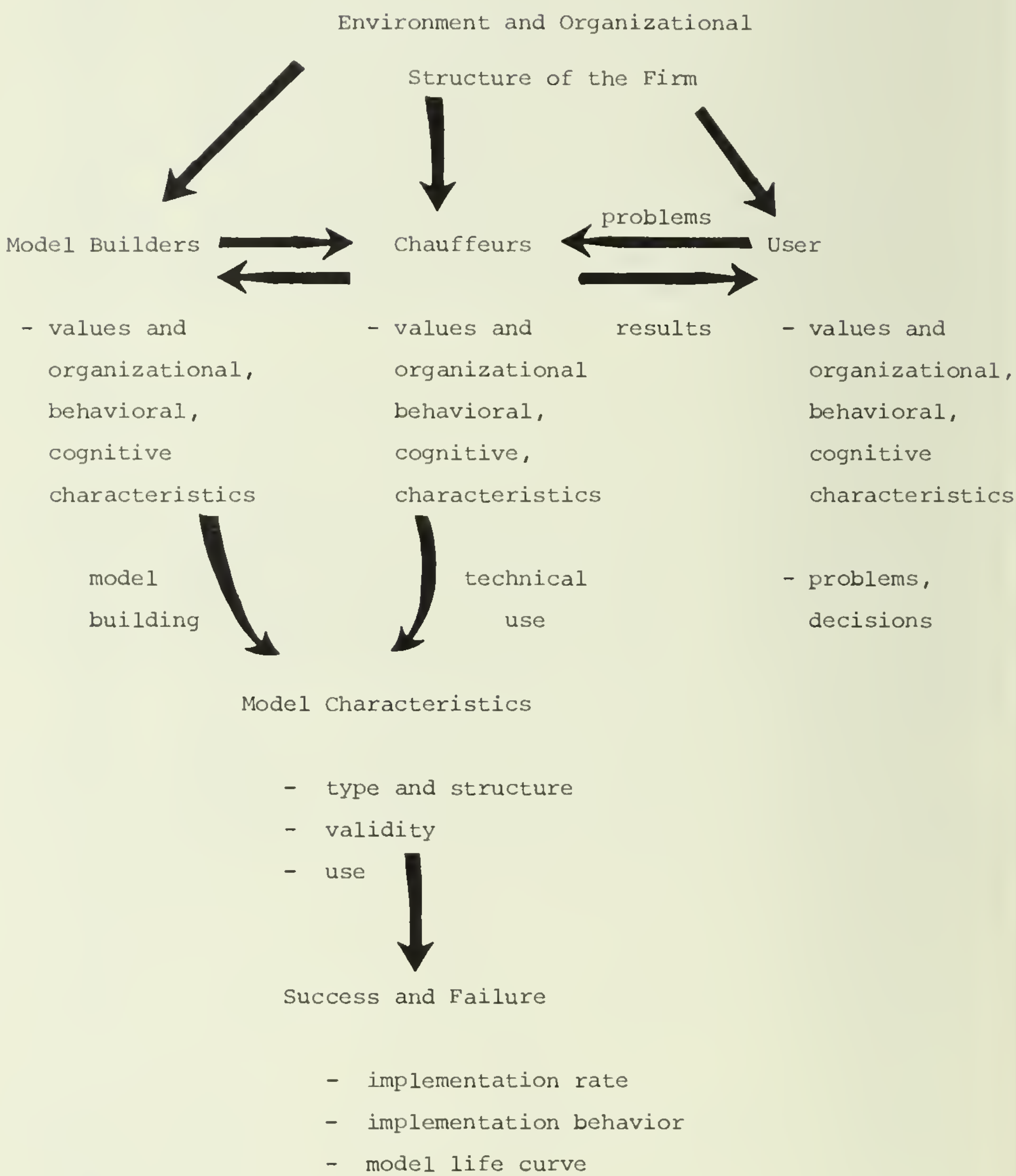
" ... plans are developed by managers who are responsible for performing multiple tasks under continuous time pressure. In this situation, there is a limited ability or incentive to explore in detail the consequences of a range of alternative decisions or the consequences of a range of alternative future environments [67, p.34]."

Due to their organizational status and their background, the situation of the model builders is different. Hall sees the following factors endangering especially the implementation of strategic planning models:

"... because of their isolation,modelers fail to capture many important facets of the strategy formulation process in the model. ...Those facets generally missed are the qualitative, skill, and politically oriented factors which dominate the actual strategy formulation process within all firms. ...The modelers view their task as one of 'getting something running,' since they will be evaluated on the basis of this 'end' product. The result is a model - often mathematically sophisticated - which is inadequate and is consequently un-utilized by general managers in their decision analysis (viz. [67, p.38], [138])."

More recent research and our own experiences described in chapter 9 have shown that the ideal of bringing the top executive directly to the computer, an information system or model has so far only in rare instances been achieved (viz. e.g. Meador and Ness [95], [4,27]). Typically, top executives or users have problems which they describe to staff personnel who then work together with the model builders on the description and solution [92, 145]. Functionally either the staff members or the model builders play the role of so-called "chauffeurs" or intermediaries: they perform the model runs and supply them to the user. At the same time, they are "exegists, confidents, crusaders and teachers" (viz. Keen [82, p.11]). Figure 2.16 visualizes how these relations influence the type of model to be built and its implementation success. Further relations must often be considered if external consultants play the role of "pioneers," "change agents" and model builders in a corporate modeling team.

Figure 2.16. Factors and relations influencing success of model



Project Team

The user of the model and his objectives have to be clearly identified. Model users and model builders often have a different perception of a given planning problem. This is caused by their functional fixedness, individual experience and cognitive behavior. The design of a corporate modeling team must ensure that the "model-manager" interface be closed. The user should be represented in the corporate modeling project team and preferably preside and finance it. Since a corporate modeling project is likely to involve several departments on the user's side, requirements and responsibility have to be defined and coordinated. Top management support should be obtained to enable the users in the project team to participate in all steps of the modeling process. Such support and participation increases understanding of the modeling system with its potential and limitations and teaches the model builders to answer relevant user questions.

Planning Process

"It is most important that the model be designed in conformity with the existing planning and budgeting process-whatever that may be (Gershefski [58, p.45])." A first rough version of the model should - if possible - substitute the manual calculation of planning alternatives and allow a quantification of benefits, such as reduction of clerical work, more and more timely information. The use of a model should be integrated as fast as possible into the corporate planning procedure of a company. Only useful results justify that at a later stage the planning procedure is adjusted to more fully exploit the potential of a then perhaps evolutionary developed model (viz. Schultz and Slevin [128, p. 34]).

Type of Model and System

By the principle of parsimony the model should be kept as simple and robust as possible, but it should be complete enough to supply the answers to important questions. One should be able to change the database and the structure of a model much faster than the environment in which the model works changes (viz. Little [90]).

Such requirements call for an evaluation of the available corporate simulation and planning systems (CSPSs), especially by the model builders, before a project is actually undertaken. Such systems and criteria of

evaluation are described in chapter 3.

The model should be designed in a modular fashion. This facilitates the understanding, maintenance and implementation of the model and decreases the dependence on one person. Furthermore, "ad hoc" and "throw away" models may be easily assembled and the modules may be used for different models.

Data

Insufficient or irrelevant input and output data either endanger the credibility of a model or threaten to "drown" the chauffeur and/or user by information they cannot use. User and problem requirements have to be clarified as far as possible before the construction of a model.

The database of a model should be designed in such a way that it may serve for different models and users. Problems of data access and security must be solved.

Communication

Reports and model descriptions should be written in a language and style which is conceivable for the user. Technical jargon creates resistances and hostility to a model on the side of the user (Doctor and Hamilton [41]).

User contacts should be formalized by defined deadlines and progress reports. Informal contacts and discussions between members of the project team, e.g. in brainstorming sessions, allow the creative generation of solutions and the exchange of problem background information. It is advisable that a "chauffeur" play the role of a team moderator. Model and systems documentation must be sufficient to allow for changes in the structure of a project team.

THE ROLE OF THE COMPUTER IN CORPORATE MODELING

Corporate planning and simulation models known today are generally programmed for a computer and use equations and logical relationships for a formal representation. This is the case although many models only map versions of already existing manual accounting, reporting and planning routines. Indeed, considering their mathematical sophistication alone, many models would not require a computer, but could be formulated and operated with pencil and paper. It is also known that the human mind with its power

of association, pattern recognition and deduction is an unequaled "device" for creative planning and imagination. Since modern computers are certainly not competitive in these areas, some planners still have considerable reserves with respect to its use combined with quantitative methods. A task oriented discussion must show what type of CSPM and mode of operation should be chosen to support a certain planning activity.

Type of Planning and Computer Support

According to a classification due to Gorry and Scott-Morton [63] Figure 2.17 shows some information characteristics for different types of planning. Certainly all types of planning require intuition, experience and fantasy. But the extent to which planning activities and the use of data and models can be decomposed into programmable and non-programmable elements is different for alternative types of planning (viz. Eilon [46], Meador and Ness [95]). The proportion of planning activities which can be supported by the computer and planning models is higher and different for dispositive and operational planning than for strategic planning.

In the first case, models may have a rather fixed structure, the linkage of submodels is programmed and the user obtains programmed solutions from regularily generated data.

In the second case, models tend to have a varying structure and model interfaces are established by mental models. A modular corporate simulation and planning system should offer ready-made submodels and methods which support and even teach isolated but frequently encoutered planning tasks and data evaluations (viz. Mertens, et al. [99, 100]).

Figure 2.15 and the previous discussion in this chapter have shown that the strategic management process possesses only very few possibilities for a formalization.

It has been noted before that as a consequence, most corporate models support the dispositive and operational/tactical or short- to middle-term planning process. Fewer examples are known in the strategic area. In the first case, a computer-assisted solution is very often competitive: the planning process involves often a high level of routine calculations using large amounts of data. The calculation of financial planning alternatives performed by the CIBA-GEIGY corporate financial model, for example, only takes but a few minutes. Corresponding manual calculations which were carried out previously took up to a man-month of a

competent planner's valuable time. He can now concentrate on problems where is competitive.

Figure 2.18 contains a list of advantages for both manual and computer-based planning. It largely depends on the planning problem and the user, where the exact boundary between the two types of activity is drawn.

Figure 2.17. Planning information characteristics

Characteristics	Operat./Middle Range Planning	Strategic Planning
Source of information	mainly from within the firm	environment
Extent/validity	large/narrow	small/large
Aggregation	low	high
Planning Horizon	short term (day/yr.)	long range (yrs./decades)
Time increment	(hour-quarter)	(yr./decade)
Actuality of data	very	often low
Units	specific:pieces, price quality, monetary units	mainly monetary units
Accuracy	great	small
Frequency of changes in data	frequently	not so often
Frequency of use of data	regularly/ad hoc	ad hoc
Regular use and changes	often	seldom, ad hoc

Figure 2.18. Manual versus computer based planning

Manual Non-Programmable Activity	Computerized Programmable Activity
- imaginative associative and deductive capabilities	- routine calculations
- non-quantifiable problems (psychological, political social)	- standard applications of sophisticated methods
- few data, few and non-routine calculations	- large amount of data and calculations
- only low accuracy and speed necessary	- high accuracy, speed and frequency of use, low error rate
	- large memory with fast access

Languages, Systems and Operation

Whereas originally in the sixties, the first corporate models were programmed in higher level scientific programming languages, predominately FORTRAN, more recently special purpose programming languages and systems have been developed for this purpose (viz. Grinyer and Wooller [64, pp. 11-14], Rosenkranz, et al. [19]).

At a minimum, such systems include a special purpose corporate planning and simulation language (CPSL) and modeling software. The language enables the user to code his own tailor-made model logic and to call on ready-made software that performs frequently required standard planning operations or management science operations and evaluations.

Corporate modeling systems were developed for a number of reasons:

1) Scientific languages like FORTRAN, APL, and to a certain extent PL/1 provide executive efficiency, good documentation and debugging facilities. However, models programmed in such a language are generally difficult to conceive for a user who has little background in programming or data processing. The identification of a user or intermediary with his model increases if he is able to understand, change and run it. Consequently, it is desirable to enable the users, as far as possible, to construct their own models. Certain technical disadvantages are accepted under these circumstances.

2) Even more technically oriented model builders may profit from the use of a corporate modeling system (viz. also [105]): they are more problem oriented and possess commands which allow the

- automatic reading from or writing to external files and an automatic storage allocation;
- the parameter controlled specification of output reports;
- the invocation of completely integrated modeling software to either perform frequently encountered planning calculations (e.g. extrapolation, interpolation, growth-rates, financial ratios) or econometric and management science methods;
- the coding of English-like programs with a high degree of modularity readability and transparency.

Using these aids, model builders may code models in a shorter time and may concentrate more on modeling than on data processing activities.

CSPMs are operated in conversational mode on timeshared computers or in batch or remote batch mode. The last five years have seen an increasing use of conversational systems and surveys indicate that more than 50 percent of the CSPMs known today are run in conversational model [64,111]. This goes hand in hand with the use of corporate modeling systems, since many are installed on bureaus timeshared computers. Also conversational programming languages like APL are used more often on either in-house or bureau computers.

Altogether, the choice of an appropriate computer support for a corporate modeling project must be determined by

- the planning problem to be solved;
- the type of user, intermediary and model builder;
- the available computing facilities.

Figure 2.19 distinguished several types of CSPMs according to the given computer support. A more detailed discussion is given in the following sections (viz. also Grinyer and Wooller [64, pp. 86-108]).

Ready-Made Models

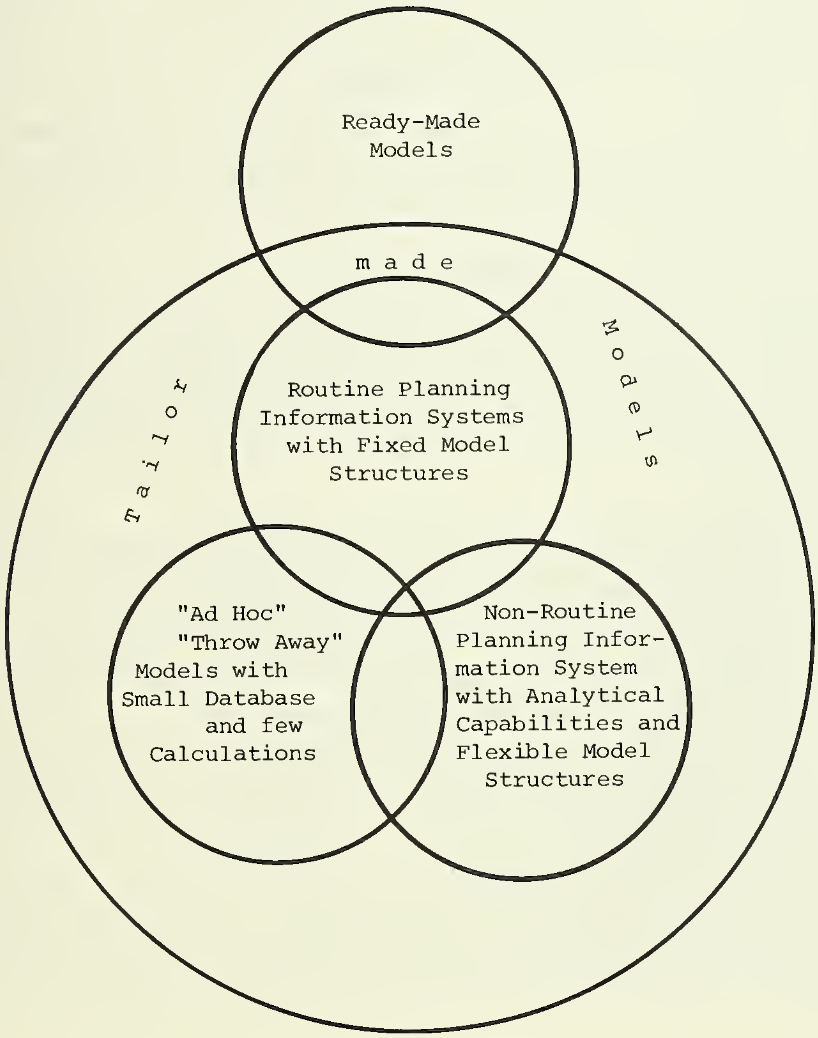
Such models possess a structure which is not specifically designed for a particular company. Examples are general models and corresponding programs for

- balance sheet calculation
- investment analysis using standardized
  discounted cash flow methods
  internal rate of return calculations
- routine trend or smoothing forecasting

Such models do not depend on special planning, accounting or controlling conventions of a company.

Because of their fixed and unspecific structure, ready-made models are often purchased from computer manufacturers or consultants. Most often they are programmed in a scientific language, like FORTRAN or even ASSEMBLER language. The user is familiar with the model and its general logic. Therefore, it is not necessary that he knows the program or is able to change it. From a programming point of view, one may thus concentrate on execution efficiency. Ready-made models may be operated on an in-house computer or at a service bureau. Especially in the latter case the model tends to be run in conversational mode using teletype terminals and a timesharing computer.

Figure 2.19. Different types of corporate models



Tailor Made Models

They incorporate a logic which is specific for a particular company which may not be transferable to other companies without difficulty.

Fixed Structure Models

Fixed structure tailor made models consist of fixed blocks of submodels, programs or modules which perform specific planning jobs. In general, they do not need to be flexible, because changes in their structure are only in rare instances necessary. The user does not need to understand their detailed logic, because the models only automate routine and regularly planned calculations, such as

- plan aggregations and consolidations;
- effects of isolated changes in the planning database;
- report writing as are characteristic especially for bottom-up activities of a planning process.

These calculations are normally documented in a planning and controlling manual for short- and middle-range planning purposes. Management decisions and an environmental analysis are generally not analyzed or simulated by such models.

"Ad Hoc" and "Throw Away" Models

They are generally small with respect to the data required and the programs to be coded. In most cases, they are designed to solve non-routine, non-repetitive planning problems in an ad hoc fashion. Often, it is required that they may be quickly formulated and solved. Typical examples are

- isolated investment studies (R&D, New Venture Analysis) which show the effects an investment has on the profit and loss statement as well as the balance sheet of an organizational unit;
- econometric product line analysis and forecasts involving only few exogenous and decision variables;
- income margin simulations for a small number of products.

Besides the speed of formulation and computing such applications frequently require that

- the user or analyst formulates and understands the model himself.

Among other reasons, this is the case because it would often take too long to obtain the appropriate data processing and management science support;

- modeling methods and software are easily and flexibly available.

These requirements may, to a large extent, be fulfilled by the available on-line modeling systems. Such systems are either installed in-house or on a service bureau computer. They are mostly run in interactive mode using teletype terminals or light screens.

Models Based on Planning Information Systems with Analytical Capabilities

The CIBA-GEIGY applications described in chapter 9 mainly belong to this class of tailor made models. Their database may be large and is in most cases kept on external storage devices, mainly disks. The structure of the models may contain up to several thousand equations, although these are in most cases of a very straightforward nature. Simple and more sophisticated modeling tools are required at the same time.

Integrated modeling software is needed for marketing analysis and forecasting, financial analysis and resource allocation.

Models based on planning information systems with analytical capabilities serve both ad hoc and regular planning activities. The systems must be very flexible to fulfill very heterogenous requirements. Inter-language communication facilities are needed to code efficient fixed structure models, dialogue programs may be required to interactively specify econometric models. Finally, the system may call for interactive programming and execution. As a consequence, it should be possible to operate models in a conversational, remote batch and batch mode.

STAGES IN MODEL DEVELOPMENT

Although corporate models support both regular and irregular planning activities for very different types of users, it must be realized that their development requires that certain common modeling activities or steps are performed.

These activities should be defined and carried out on a planned basis. A corporate modeling system should support such activities and modeling steps as far as possible. In the following paragraph a multi-step design procedure is outlined which should be useful in most cases. It incorporates design steps as they have been formulated by Fisher for models based on planned data [50], by Wold, et al. for the design of econometric models [103, pp. 6-13] and Cohen and Naylor for the design and experimentation with simulation models [35, 101,107].

The steps are carried out in a dynamic feedback fashion [37]: If the result of a step is not satisfactory compared to the objectives formulated in the first step, it must be revised or several steps have to be carried out again.

1) The intended use of the model has to be specified, i.e. it should become clear in this step if the user wants the model for forecasting, planning, optimization, general exploration or only as a training and theoretical test device. If several aspects are of importance simultaneously then priorities have to be weighted somehow. The output, input and decision variables of the model together with some indication of their relationshops should be listed. The type of questions the user wants the model to answer together with the time horizon and time scale of the model should be defined.

2) The nature of the input and output data has to be investigated. This incorporates an analysis of how, where and by whom input data are collected, stored, and up-dated, how accurate these data are (e.g. panel data or fully collected data, bias and measurement error) and finally how data are related and structured (e.g. tree-structures and levels of aggregation) and how they should be presented. The nature of the output data has to be established accordingly.

3) The equations of the model that relate the variables have to be formulated. Their nature, structure and relationships to other equations have to be explored. Parameters used within the equations have to be defined. A graphical representation and plausibility analysis of the model structure should be performed.

4) The model has to be coded into a computer. An evaluation of the available programming languages, especially corporate simulation and planning languages, should lead to a decision that is compatible with the methodology chosen, that facilitates the formulation, running and debugging of the model and guarantees some ease of model-user communication. The possibility of employing hardware devices such as teletype terminals and light screens has to be explored.

5) Unknown parameters of the model must be estimated. The fully estimated model has to be solved. Different estimation, solution and simulation methods have to be tested and investigated.

6) A model that has been programmed into a computer has to be tested and validated. How this goal is achieved depends to a very large

extent on the intended use of the model and the nature of its data and equations. Validation activities might include plausibility checks and tests on a priori knowledge one possesses about the firm and its environment. Statistical verification testing may be used with models based and estimated from historical information. Finally, one may try to predict the behavior of the firm and to compare the outcome of a model run either with historical data (historical verification or retrospective predication) or the forecasted data with newly measured data (verification by forecasting or prospective prediction [106, 107,101]).

7) After the model has been validated or parallel to its verification by forecasting, one might start using and implementing the model. As with the model design, it is also advisable to use a model on a planned basis. This is especially true if the model user or policy maker wants the model to answer a number of interrelated "What if?" or "What to do to achieve?" questions by choosing values for his decision variables and target values for the endogenous our output variables. In the case that the user poses his "What if?" questions to gain a "feeling" for the response of his output variables or an objective function and their robustness [112] to entrepreneurial decisions, these questions could be posed on a planned basis as much as possible. Alternatively, if the user defined target values and is interested in the relation between the target values and the necessary values of his decision variables to achieve the former, such relations may be investigated with different methods of varying effectiveness.

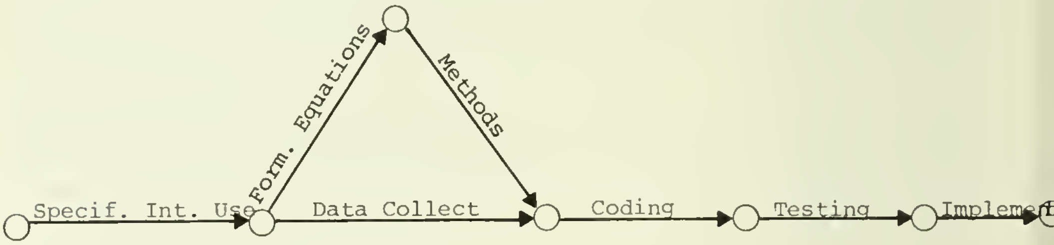
CONCEPTS OF CORPORATE MODELING

The multi-step model design procedure outlined in the previous section is largely self-explanatory and is often automatically implied when one constructs a computerized scientific model on a planned basis. In chapters 4 through 8 these steps will be described in more detail for the construction of corporate models.

PROJECT PLANNING

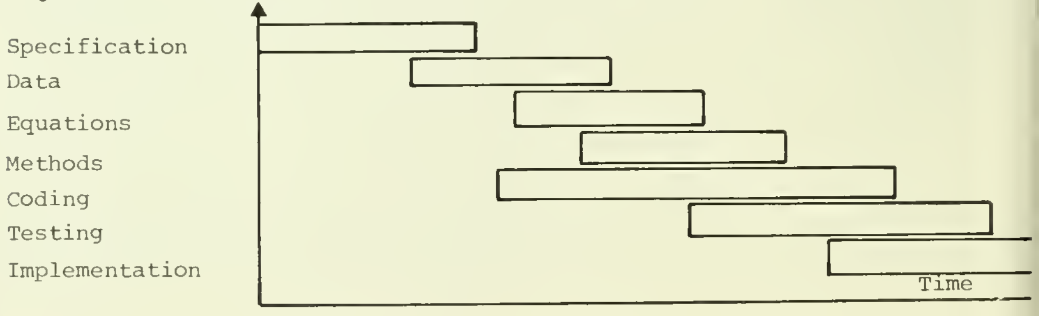
Planning a corporate model does not only imply that a logically and practically sound structure of the design steps is established, but also that some time, capacity and cost planning is carried out for a project. Although the number, complexity and duration of the activities that constitute a corporate modeling project are not likely to be as large, great or long as encountered with the scheduling of large industrial projects, the application of formal project planning methods may be advisable. Figure 2.20 shows an example of the type of project network which could serve as a basis for project planning.

Figure 2.20. Simplified project network for corporate modeling projects



The network shown corresponds to the event-oriented graphs as are used for such proejct planning methods as CPM (Critical Path Method) or PERT (Program Evaluation and Review Technique). The figures on the arcs indicate estimates of the time required to carry out the different modeling steps. A number of other techniques are available for the same purpose, e.g. one could use simple Gantt-charts as indicated in Figure 2.21 to carry out time and capacity scheduling for project team members of model segments.

Figure 2.21. Gantt-chart for project scheduling



It should be noted that the different modeling steps may have a different weight in alternative applications. Also their sequence is not necessarily logically compelled. For example, the specification of the intended use of the model may lead up to a decision on which programming language is going to be used for the computer coding. The actual coding may then be carried out in parallel with the data collection and preparation, the formulation, estimation or solution of model equations. One could also say that it is part of the specification of the intended use to define standards which have to be met in all the modeling steps. Hence, every modeling step would involve a validation in which primary objectives and achievements are compared. Deviations could then lead to corrective actions. Also the circumstances under which a model is constructed may influence the sequence of model steps. Such differences may arise, for example, from the type of modeling problem encountered, the number and composition of a corporate modeling team, or deadlines that have to be met during the construction of a model. However, in all applications it seems to be advisable to clearly define the necessary modeling steps and their interrelation and duration.

COSTS

Depending on the user's objectives, a corporate modeling project may require from several man-weeks up to several man-years for its realization. It does not seem to be sensible to define an average project effort or costs under these circumstances. Experiences at CIBA-GEIGY indidate, however, that the construction of a top down middle-range or short-range financial planning model requires something in the order of six to nine man-months of effort. Such a model typically deals with tables describing balance sheets, profit and loss statements and financial key figures as well as relations between them. In a typical case, one may deal with in the order of a hundred tables describing different organizational units on different levels or aggregation. This rough estimate is based on the following assumptions:

- a corporate modeling system is available and that either the users or model builders are familiar with it.
- a planning process has generated well defined historical and plan data which are available for modeling purposes (i.e. only a very small effort is required for data definitions and collection, input-output

definitions according to specifications of the planning process).

Marketing and product oriented income margin simulation models seem to require a similar effort. Integrated models which simultaneously deal with finance, marketing and production or resource allocation tend to require a much higher effort. Investigations seem to be more reliable and consistent with respect to estimates of the distribution of efforts on the different modeling activities.

In the first investigation questioning 323 American companies of whom 102 possessed a model, Gershefski in 1969 obtained the following figures for the manpower distribution over the modeling steps [57, p. B-311] described earlier.

Figure 2.22. Corporate modeling project: distribution of effort

25%	Definition of general approach (step 1)
25%	Collection of analysis of data (step 2)
40%	Development of computer program (steps 3-6)
10%	Implementation (steps 6-7)

In an investigation published in 1975, Grinyer and Wooller (65 British companies) obtained the following cost-percentages for different activities performed and resources used [64, p.22]:

Figure 2.23. Corporate modeling project: distribution of effort

21%	Feasibility study
27%	Programming
17%	Implementation
35%	Other
65%	Manpower costs
10%	Consultancy costs
25%	Computer costs
100%	Total Costs

In summary, it seems realistic to attribute in the order of 50% of the effort and costs required to the first two modeling steps. These two steps depend to the largest extent on the objectives of the user and a correct project organization.

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FOOTNOTES TO CHAPTER 2

1. Parts of this chapter have originally been published in a paper by the author [122] entitled "Methodological Concepts of Corporate Models". Proceedings of the conference "Simulation versus Analytical Solutions for Business and Economic Models", W. Goldberg Ed., Gothenburg 1973, BAS No. 17, pp. 59-91.

2. Usually, these vectors are defined as column-vectors. For writing convenience they have been transposed.

3. In the literature several definitions of stability are used. For the sake of simplicity Samuelson's definition of perfect stability for the first kind has been used [126, p. 261).

Data

INTRODUCTION

A solution of a corporate model, that is , the determination of its endogenous variables in time, becomes possible only after first, the variables and the structure of the model have been specified, and second, numerical values for the input variables of the model have been supplied. Input variables to a model are the exogenous variables and the decision variables. The latter are, by the definition, determined by the model user. Depending on the analytical form of the model (i.e. algebraic or difference equations) and its intended use, it is further necessary that the values of model parameters and initial or target values of the endogenous variables are known before the model can be solved. The model parameters may either be supplied from the outside or be determined within the model in an estimation step that precedes the solution step in the model design procedure.

Symbolic information regarding input variables, parameters, and initial or target values is called input data to a model. Information dealing with values of endogenous variables or internally estimated parameters is called output data. Both types of data are in most cases arranged in series (normally time series or cross sections) of numeric data. These series are assigned symbolic names by the model user. The corporate model is expressed in equations that have to be solved in such a way that algebraic evaluations are carried out over defined lengths of the series during a model solution.

Input data as well as output data possess certain properties which seem at least worth a short investigation, especially because, to our

knowledge, they have not been discussed explicitly in the corporate modeling literature yet.

The main difference between input and output data results from the fact that numeric values of the latter are calculated, measured or sampled within a model, whereas numeric input data are collected, calculated, measured and determined by the user outside the model. Apart from this basic difference, one can investigate the properties of model data from a number of different viewpoints. Some of these notably deal with

- numeric or non-numeric (e.g. character) data,
- experimental or non-experimental data.

It is of further interest to investigate

- how model data are collected and classified,
- where they come from and how they are used,
- what their relation is with respect to a time scale and,
- how they are treated and stored in model calculations.

INPUT DATA

NON-NUMERIC-DATA

Non-numeric information in the input data is mainly contained in the model structure and symbolic notation used to designate model variables or groups of variables. In most corporate models, little attention has been given to the possibility of expressing non-numeric information about the model structure in terms of the symbols used to denote variables or equations. The same is true for most of the available corporate simulation and planning languages. It was, therefore, overlooked that model calculations may frequently be carried out more efficiently, provided that evaluation of the non-numeric data is achieved, before any arithmetic calculations are performed.

This point may be demonstrated by the following examples. Consider a firm which is made up of several operating divisions which produce and sell their products in different countries. Assume further that within a division one has several subdivisions which concentrate on the production of certain classes of products. For instance, the "Chemicals Division" of a multinational firm might contain the "Organic" and "Inorganic" subdivisions. Because it is assumed that the firm produces and sells in

several geographic regions, the activities of its divisions in a certain region are controlled by a subsidiary company. The organization and operation of the latter may be strongly influenced by its environment. So one could imagine a different legal and financial organization of the companies as a result of different national laws, taxes and capital markets. In the case where basic input data are detailed according to company, division and subdivision, one could rank all the information on a three dimensional nominal scale as is shown in Figure 3.1.

A variable that is common to all divisions, companies and subdivisions, such as a variable contained in an income statement, may thus uniquely be identified by a symbolic notation such as

Variable-Name ABC.

It is again possible to code a great deal of non-numeric model information into the name of the variable. Assume that the variable is contained in an income statement. Then one can imagine that it may further be detailed according to such scales as

- product,
- age, (old, new),
- market sold to,
- strategic raw material needed,

as is shown in Figure 3.2

The scale used in Figures 3.1 and 3.2 may either follow by definition (e.g. divisions, companies) or by measurement and data analysis. An example of the latter could be the market scale. If the markets are made up of certain types of individuals or customers then the nominal scale could follow from a classification of market data (viz. Aaker [1], Green, Tull [32], and ref.) Several firms have started with the application of classification methods. A short description of some examples will be given later in this chapter.

It is well known that non-numeric information, as has been described above, may be converted to numeric information on an ordinal or cardinal scale using appropriate scaling methods [1,32,70,71]. In fact, this is very often done in practice whenever one or several digits of a variable code are used to express a nominal scale on a mostly unit increment interval scale (e.g. divisional division 2,...). It is also common practice to combine various nominal scales with cardinal scales to identify model data. In Figures 3.1 and 3.2 this would be the case if one introduces a further dimension to express that data are collected over time.

Figure 3.1. Input data and nominal scale

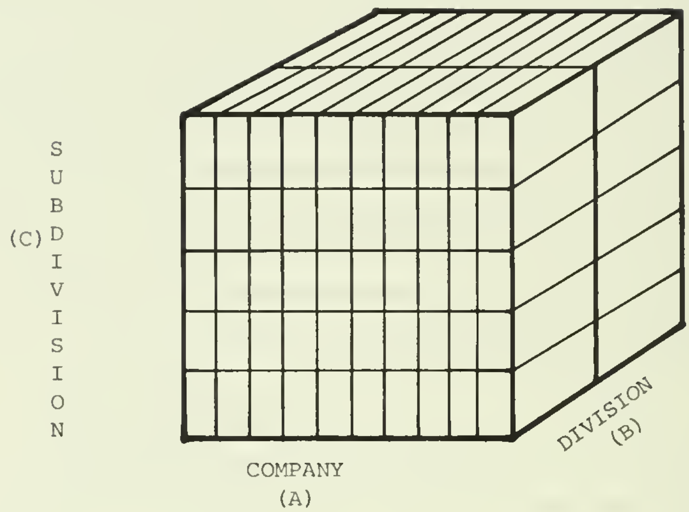
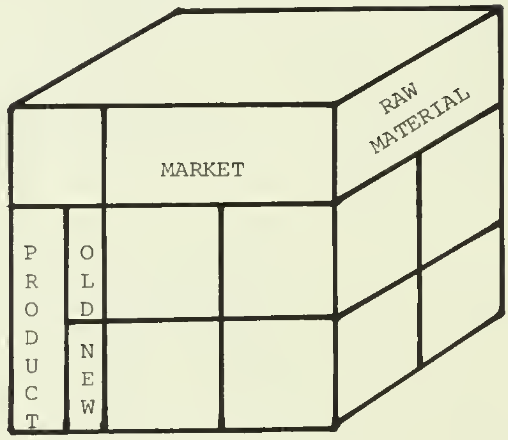


Figure 3.2. Input data and nominal scale



USE OF NON-NUMERIC INFORMATION

Interesting for practical applications is not the fact that variables can be denoted by symbols that allow their classification on a nominal scale, but that it is in many instances possible to express the relationships between variables and parts of the model logic in that notation. Some consequences of this property have already clearly been seen by Mattesich [53, pp. 448-465]. However, it seems that little use of such concepts has been made in practical modeling.

If one defines that all model variables form a set consisting of distinct elements, then one can imagine that this set may contain certain subsets that are made up of elements or variables with common properties. Such subsets could be formed by divisional or company variables of a model, other subsets might contain variables of the balance sheet or the income statement. One can also imagine subsets of marketing, production or financial variables. Although it is obvious that such specific definitions are not necessary to construct and solve a model, it is equally clear that set definitions and operations with sets speed up the model construction, computer coding and solution considerably. As a side effect the user obtains a much tidier and more transparent model representation both from a notational and graphical viewpoint.

It is possible to demonstrate these points with the examples chosen for Figures 3.1 and 3.2. Assume that one has denoted the set of all possible consolidated income statements or "tables" of a model on the divisional, subdivisional and company level by

INCOME (ABC).

If all elements contained in the set A (company), B (divisional), C (subdivision) are well defined, the symbol

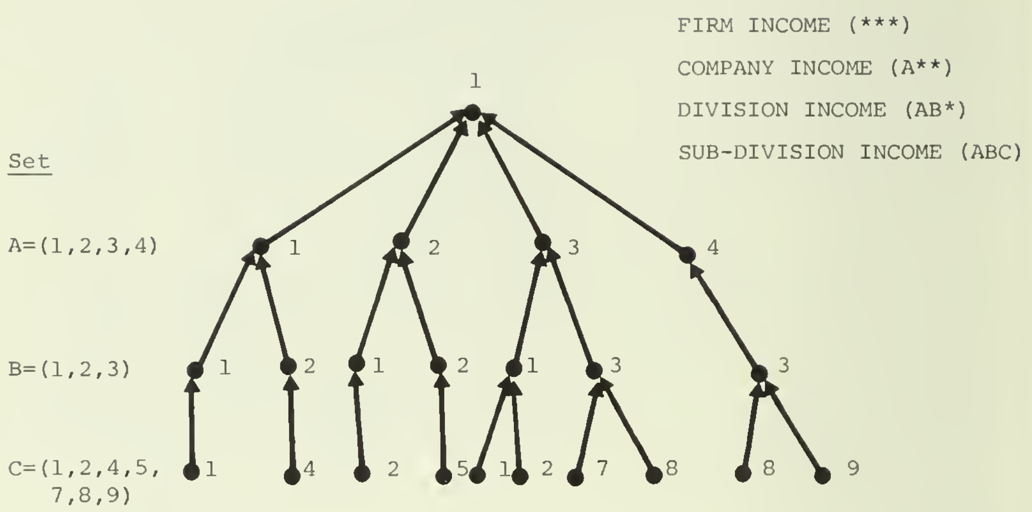
INCOME (AB*)

could indicate the income statement of a certain division in a certain company, similarly

INCOME (A**)

would indicate the income statement of a certain company. Since these income statements follow from an aggregation of the income statements on the subdivisional or divisional level, respectively,the symbols at the same time classify the variables and the sequence of their calculation (viz. Figure 3.3).

Figure 3.3. Tree structure of model variables



The nodes in the tree (Figure 3.3) represent the model variables, arcs connecting nodes express the sequence of the evaluation of the mcdel variables and simultaneously a cause and effect relation. From the graph one sees that a change in the income statement of subdivision number four, will affect the income statement of division two, company number one and the income statement of the total firm. One would often obtain similar structures if the variables, their relationships and the flow of calculations for the data classified in Figure 3.2 were expressed in the same fashion. One can show in general that a "recursive model," i.e. a model in which cause and effect relations may be distinguished, can be represented graphically by a tree like Figure 3.3. This will be discussed more thoroughly in chapter 5. A tree is a special so-called acyclical graph. One of its percularities is that all nodes can be numbered systematically in such a way that the initial node of an arc always carries a smaller number than the final node. In Figure 3.3, nodes and their identification correspond to variables in a model. Since the symbols used to identify model variables may always be converted to a code consisting of natural numbers, the practical consequence is that cause and effect relations as well as the flow of calculation in the solution step of the modeling process may uniquely be seen from the code. Another very

important consequence is that with corporate simulation and planning languages (CSPL), which have such languages as ASSEMBLER or PL/1 as source languages, very efficient tree calculations may be effected by the use of based variables and pointers.

A number of other advantages follow immediately, if one performs set operations explicitly. Let A be the set of variables of all the subdivisions of the firm on a worldwide basis, let B and C be the set of variables of the subdivisions in the USA and Europe, respectively, and let D be the set of variables attributed to division number one, then the expression

(3.1) $E = B \cup C$

would denote variables of subdivisions either in the USA or Europe (union),

(3.2) $F = E \cap D$

variables of subdivisions in Euorpe or the USA that belong to division number one (intersection),

(3.3) $G = A - F$

variables of subdivisions that do not at the same time belong to division number one and are situated in Europe or the USA (difference). It is a big advantage if corporate simulation and planning languages allow for much tree and set operations.

NUMERIC INFORMATION

Numeric input data for the variables and parameters of a corporate model will in real world situations in general be non-experimental, because economic reasons in most cases forbid any experimentation with the real system. This is a difference to output data which may be generated on a planned basis using sensitivity analysis and experimental design techniques [21,22,49,51,63].

Numeric input data are either obtained by measurements, forecasts or decisions and guesses of the model user. Measurements are typically used for the historical values of all model variables and the model parameters. *Ex ante* forecasts have to be supplied for future values of exogenous variables. Future values of the decision variables and target values for the endogenous variables are specified by the model user. Although this is no necessity, input data to a corporate model usually

do not quantify reactions of the firm's surroundings to its decisions.

Measurements or forecasts may follow from a statistical sample or just by judgement sampling and guesses. In both instances, data will incorporate measurement or forecast errors.Normally a corporate model will be based on both types of measurements. Examples for data that follow from statistical samples and forecasts based on statistical samples are the values of macroeconomic exogenous variables or the values of marketing variables that follow from consumer panel data. The firm may often obtain such data from the exterior through such organizations as government agencies or consulting bureaus. Other data may be sampled statistically within the firm. An example would be a delay parameter describing the expected time between product delivery and payment of the customers, measurements of inventory levels, invoice amounts or employee absences. The firm may also generate the forecasts of the exogenous variables internally.

SAMPLE DATA

Statistical samples are usually taken with a well-defined method, such as random or stratified sampling. On this basis, it is at the same time possible to determine and control the accuracy of sample characteristics such as means and variances by their empirical values. As a consequence, it is often possible to express the risk connected with a decision based on sampling results numerically. From sampling a number of invoices, it is possible to construct a confidence interval for the mean or the average invoice amount. It is then possible to calculate the probability that the true mean will be within similar confidence intervals that result from other sampling experiments. Similarly, one can often regard measurements of a time series as a statistical sample, fit a special model to the data and make probability statements with regard to other possible samples and forecasts after some assumptions about the distribution of the residuals have been made. For problems in which several independent exogenous or decision variables influence an endogneous variable, one may, in analogy, construct confidence regions relating changes of the endogenous variable to changes in the other variables (viz. Churchman [17]).

With judgement samples or guesses or parameters and variables, it

is not possible to obtain a link between probabilities and confidence intervals or regions other than subjectively. Very much here depends on the skill, experience, knowledge and subjective preferences of those people who supply the data. Unluckily, enough from a methodological viewpoint, many data needed to run a corporate model are likely to result from judgement samples or expert guesses. Especially in two situations such data may be the only ones available: first, if the sampling process itself would be very costly or if it would disturb the firm. Second, if meaningful samples cannot be defined because the data are generated under very different circumstances as would be the case whenever the firm's decisions change environmental data.

ACCOUNTING DATA

One may list practically all the accounting and budgeting data available for the input to the financial segment of a model under the first category. As Mattesich states "accounting can be regarded as an applied, normative discipline. In budgeting, the normative aspects of our discipline are clearly revealed, but even the measurement of past events is closely tied to future expectations (e.g. valuation by discounting future yields) and ultimately serves goals which obviously involve value judgements [53, p.12]."

(viz.also Churchman [17, pp. 321-338]). If these value judgements remain stable over time and if the purpose of their generation does not conflict with the intended use of the model, then some accounting data may be used like time series data in an econometric model. Changes in the valuation of model variables that cannot be quantified lead to erroneous data. Such errors in the accounting and budgeting information are normally disguised by the habit of specifying far more than the significant digits in all the numbers. Furthermore, the fact that the sums of debit and credit transactions match each other exactly creates something like a "pretended functional accuracy" (Morgenstern [56, p.79] , author's translation). As with budgeting and planning systems, corporate models in general do not describe individual business transactions as they are recorded in an accounting system. In practically all cases known, data were accumulated over the basic time unit (e.g. year, month) of the model. Morgenstern remarks in this connection that

"... it must now be realized that combinations of financial statements yield far more limited information than is assumed by the nature and

extent of the numerical operations carried out with these figures [56, p.84]."

The valuation of depreciations, royalties and good will in a balance sheet or income statement can be influenced decisively by personal preferences, monetary objectives or traditions. To carry out sampling experiments with accounting data contained in balance sheets and income statements by creating a kind of impartial observer and measuring the values of the variables repeatedly at different times would certainly be very expensive indeed and would also disturb the normal functioning of the firm.

JUDGEMENT SAMPLES AND GUESSES

Equally important for practical applications is the case in which the circumstances under which data are generated are not comparable. In this instance, data have to be supplied by judgement samples or, even more important, by mere hunches. Data problems of this nature arise with internal data if the organization and technical transformation process of the firm or its information processes are changed as frequently happens in mergers, reorganizations or if new information systems are introduced and no transformation relationships between the data can be established. The same may be true for data that relate variables of the firm to its environment. In cases where within a period of ten years more than half of the products of a firm that are supplied to the markets will no longer exist in their present form and will have to be substituted, statistical samples and also judgement samples often lose their meaning.

It should be noted that at present the majority of corporate model users seem to test the effects of guessed input data on the model output by a series of deterministic "What if?" experiments.

With these experiments one does not seem to attribute subjective probability estimates to different values of the input data. Nor does one pay much attention to the questions of experimental design and analysis of model results.

Both these shortcomings will possibly be improved in the future when guesswork is accomplished more formally (viz. Hogarth [42]) and when techniques of experimental design are more commonly known.

At present, however, there seems to be little reason to give much

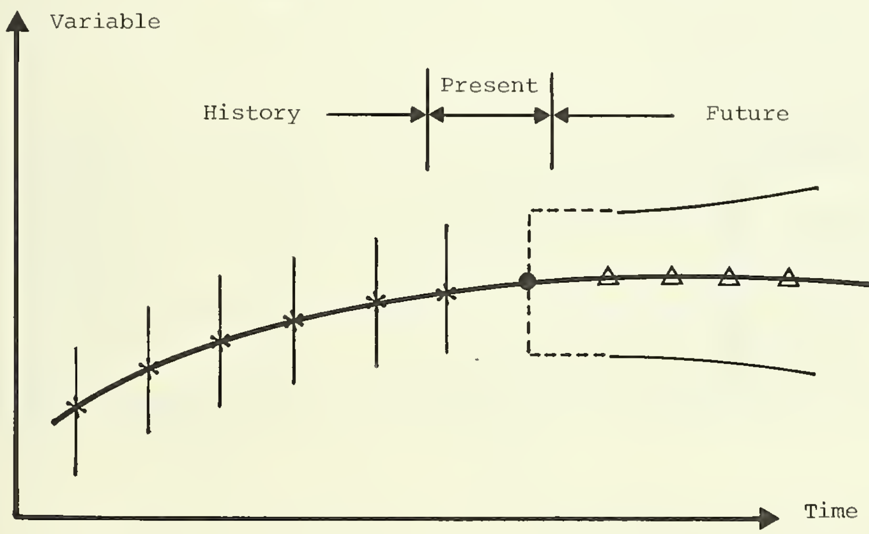
confidence to the results obtained from an application of methods of scientific guessing techniques from a formal methodological viewpoint. In practically all applications, any empirical validation still seems to be missing. Also their practical implementation still poses a number of serious problems [(25,77]. But as Cantley contends,

"There is even less reason to suppose that technological invention, development and change will suddenly stop. On this basis of being the lesser of two great improbabilities, technological forecasts are of value for enhancing awareness of likely or possible future environments, and hence for increasing our ability to realize or prevent future events according to our objectives [16]."

TIME SCALE

Model variables are usually related to a timescale which may roughly be divided into the past, the present and the future (Figure 3.4). Database evaluations concerning the past and present status of the firm have been called "What has been?" and "What is?" investigations. "What if?" and "What to do to achieve?" questions usually concern future developments.

Figure 3.4. Model variable and time relationship



For the past, a model user possesses numerical values which are either measurements or guesses together with an either estimated or guessed indication of accuracy. Future values of a variable are either forecasted or guessed. In both cases, one has to take into account risk and uncertainty in the form of an estimated or guessed confidence interval. With decision variables, the interval shown in Figure 3.4 would describe the range in which a model user may vary their values. In the case where non-quantitative policies (Tinbergen [78,p.3]) are expressed in a model numerically, one should be able to take into account boundary regions with decision variables, confidence regions with endogenous or output variables.

It depends on the definition, whether the present in a model is treated like the past or future. Provided that the basic time unit of the measurements corresponds to the interval of model solution, only one of the two definitions is used. If, on the contrary, measurements are recorded in smaller increments than the solution interval of the model, the present becomes a separate category, since parts of it may be known, others unknown.

Figures 3.5 shows the structure of data records as are used to store numeric values of variables in a CIBA-GEIGY COMOS model (viz. chapter 8).

Figure 3.5. Organization of COMOS data and variables

	PAST	PRESENT	FUTURE
Variable Name Codes and Specifications	Measurements		Optimistic Values
	Model Values		Expected Values
	Measurements Errors		Pessimistic Values

A variable number of fields may contain different values of a variable for the past and the future. This allows the storage of different model runs, differences between runs and historical measurements. The records are flexible enough to store the type of information which has been discussed above.

The values one obtains for measurement, measurement errors, model values, forecasts and forecast errors critically depend on the hypotheses used in the measurement and modeling procedure. Figure 3.5 is basically a one-dimensional approach to data representation [45] as has been used in many economic discussions and practical sensitivity analysis applications based on the "ceteris paribus" clause. The interdependence of measurement and forecast errors of several model variables may thus not be expressed. This is clearly a limitation and an unresolved problem (viz. [17, pp. 123-129]).

OUTPUT DATA

Output data of a corporate model mainly contain information about the endogenous variables. As with input data, one might again distinguish between non-numeric or structural information and numeric information. Since the output variables are usually already identified together with the input variables and the model structure, not much can be said in addition to the preceeding chapter. In a graphical representation, as has been used in Figure 3.3, nodes that have arcs incident upon them correspond to output variables, whereas nodes representing input variables have only arcs incident from them. It should be noted that from a given set of input variables it is possible to generate different sets of output variables depending on the model structure specified. Here again attention should be paid to the code design which is used to identify the variables. A code that is flexible enough to allow the construction of different tree structures and output variables may greatly improve the conceptual framework and computing efficiency.

With numeric output data, one has to distinguish, according to the modeling steps proposed in chapter 2, whether the data are generated in the estimation, solution or simulation step, in the validation step or, finally, in the implementation and experimentation step of the modeling

procedure. It should be noted that the results obtained from these steps may necessitate the formulation and decisions on additional problems and requirements concerning input data. The database of a CSPS must be flexible enough to allow for such changes.

In a statistical estimation step, model values of the endogenous variables are generated together with estimates of model parameters and the statistics related to the distribution of single parameters, groups or parameters, the stochastic disturbances and explained as well as residual variance of the endogenous variables. For output purposes, the model results may be stored as indicated in Figure 3.5. The parameters are stored separately, the statistics are usually printed out to allow a diagnostic checking and reformulation of the hypotheses used in the estimation step.

In the solution or simulation step, all model equations are solved once or repeatedly under either statistically or deterministically varying conditions with known model parameters over the stages specified by the user.

Forecasts of the endogenous variables together with confidence intervals may be obtained from the statistics which are generated in the estimation step and known forecasts or decisions for the exogenous or decision variables, respectively. These results may be stored as shown in Figure 3.5. If the estimation step is omitted, as would be the case in a completely deterministic model, subjective optimistic or pessimistic values of the endogenous variables could be generated with given hypotheses regarding the parameter values or objective function in an optimization. For repeated model solutions or simulations attention should be given to the storage requirements that result if not only summary statistics like means and variances of variable values are kept at a certain stage, but also the results of individual runs have to be retained for further evaluation in either the validation or experimentation step.

While data input and the model database should be organized in such a way that the "model-user interface" in all steps of the modeling process, especially the implementation step, does not pose any serious problems, the organization of output data obtained from a corporate model forms a basis for management use. Some examples of model output needed for this purpose are listed below:

Financial Reports

- income statements
- balance sheets
- financial ratios
- flow of funds summaries
- capital investment schedules
- tax reports

Marketing Reports

- research and development expenditures
- sales
- advertisement expenditures
- distribution expenditures
- product selling prices
- raw product prices or costs
- marginal income

Production Reports

- capacities and slack
- inventories
- employment figures

Depending on the organizational structure of the firm, its markets and products, it may well happen that a hierarchy of up to several hundred different output reports from a corporate model are of interest. Only in very rare cases are these reports likely to be of interest simultaneously; but even if they are asked for only selectively, attention should be given to their fast, flexible and comprehensive generation.

CLASSIFICATION OF DATA

With respect to data problems, corporate model builders often have to navigate between Szylla and Charybdis: relevant input data may not be readily available and the danger is great that both model builders and users will drown in a sea of irrelevant input and output data. On the one side, a model should give answers to important questions, on the other side, it should use data and variables as parsimoniously as possible.

Practitioners in this situation frequently refer to the famous "twenty-eightyrule": 20 percent of a category account for 80 percent of the result. Examples which are often given for this rule are the percentage of products or customers of a firm and their sales, costs, or profit contribution. Similar observations may frequently be made with respect to model data and variables. In the following section, a combination of formal and informal methods will shortly be discussed which may aid in a relevant classification of data and variables.

TYPES OF DATA

The preceeding chapters have given several examples for data classification. Most of these were definitional and self explanatory. Examples of data contained in the database of a model may be:

Functional Area Data

Marketing-Output

- macro economic data
- buying industry information
- customer data
- competitor data

Marketing-Input

- macro economic data
- selling industry information
- equipment and raw material data
- personnel and labor statistics

Financial Information

- exchange and interest rates
- inflation rates

Production Information

- capacity data
- technological coefficients

These data may either refer to a firm's environment or its internal strucutre. The latter may be classified with respect to its legal organization, e.g. parent and subsidiary companies, or its product

structure, e.g. divisions, subdivisions, product groups. Finally, one could distinguish between a planning structure and strategic, tactical and operational information. Several authors have more recently discussed possible classifications to be used with strategic databases (viz. Ansoff [6], Cleland and King [19k48], Ziemer and Maycock [80], Neubauer and Solomon [59]).

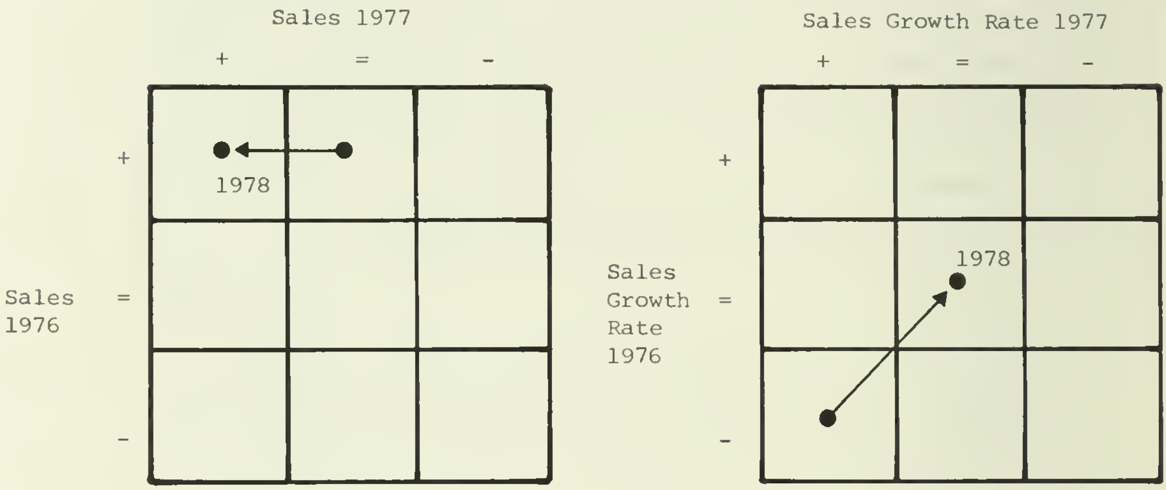
The classifications given above are not problematic by themselves, but by their content: which are the important macroeconomic time series, buying and selling industries or customers? How should products or product groups be classified for strategic planning purposes. On which raw materials should one concentrate for operational planning purposes?

The answers to these questions may often be given from the firm's information systems: sales data allow one to determine and rank, e.g. the customers or buying industries which account for 80 percent of sales. A data bank containing panel data on competitors permits the classification of the main competitors by market share in a given region. Finally, the evaluation of a standard costing system yields the most important raw materials by price and volume.

SEGMENTATION OF IMPORTANT CUSTOMERS BY GROWTH [5,61]

So-called Benjamin matrices are used in Figure 3.6 to identify important customers in a 3x3 classification. A quantity X is used to denote increases in sales by volume, value or growth rate. For a growth rate greater than +X, the (+) classification applies, for a growth rate between +X and -X the (=) applies and for a rate less than -X the (-) classification applies. The larger the value of X chosen, the more customers will be contained in the (=,=) field. Nine types of model variables may be used to describe the development of customer groups depending on pricing and advertising strategies of the firm.

Figure 3.6. Benjamin Matrices



SEGMENTATION OF PRODUCT PORTFOLIO

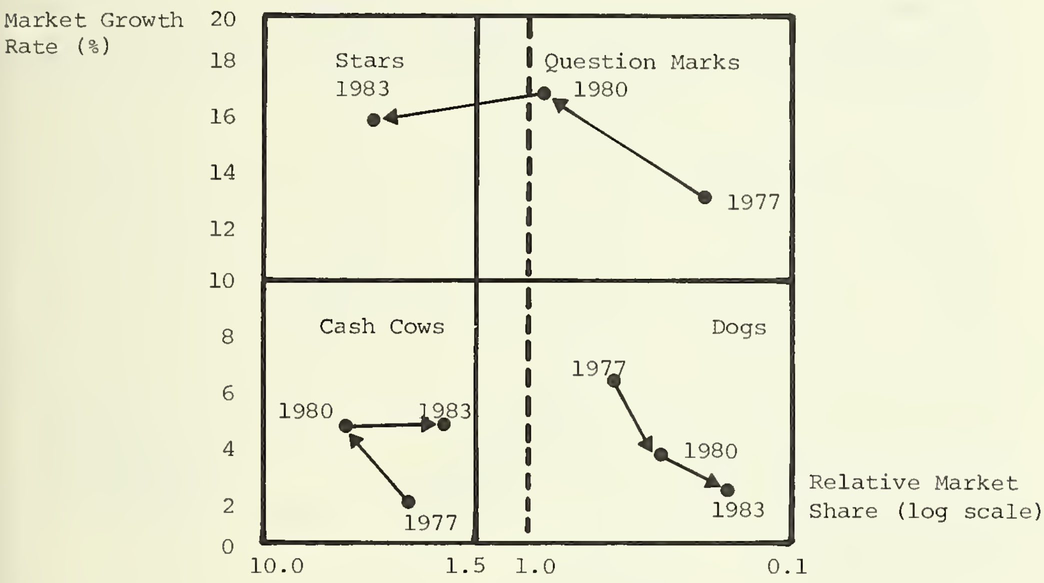
By analyzing industry cross-sectional data, Buzell, et al [15] reached the very general but also controversial conclusion that products having a high relative market share either already bring ("cash cows" in slow growing markets) or have the potential to yield a high return on investments (ROI/ROC) or capital ("stars" in fast growing markets).

This and similar observations caused members of the Boston Consulting Group (viz. Henderson [37], Hedley [33,34]) to propose a 2 x 2 classification of products and product groups for strategic planning purposes as is shown in Figure 3.7. The scale of relative market shares is defined with respect to the largest competitor. A relative market share of 1.5 indicates that a given product has a market share which is 50 percent bigger than its largest competitor. The market growth rate refers to a total product market; ten percent would be an average growth rate. It should be noted that the definition of the four "business field" quadrants in Figure 3.7 is to some extent arbitrary.

Based on the product classification, some authors (e.g. [34,80,40[) recommend a management of a product portfolio by investments, pricing and production strategies in such a way that as many products as possible become either "stars" or "cash cows." This mainly applies to products in

the high-market-growth-rate/low-relative-market-share quadrant. Divestment strategies are usually recommended for low-market-growth-rate/low-relative-market-share quadrant ("dogs").

Figure 3.7. Portfolio classification



A number of firms use this classification as a basis for quantitative modeling [80]. Based on empirical observations of average unit cost descreases with increasing cumulated production, experience or learning curves are employed as basis for the modeling [9,40,80]. Figure 3.8 exhibits an example. It is assumed that average unit costs per unit y_{1t} are described by the double-log model

$$y_{1t} = a_0 \cdot y_{3t}^{a_1} \tag{3.4}$$

where

$$y_{3t} = \sum_{t'=1}^{t} \Theta_{1t'} \tag{3.5}$$

defines the cumulated production of a product at time t as a function of production decision $\Theta_{1t'}$, $t' = [1,t]$ since the introduction of the product into the market. The parameters a_0 and a_1 have either statistically or subjectively to be estimated from historical data (viz. chapter 6). Unit market sales prices y_{2t} are often described by

$$(3.6) \qquad y_{2t} = a_2 \cdot y_{3t}^{\;a_1}$$

where a_2 may again be estimated from historical data. The experience factor or elasticity a_1 is assumed the same for both models and corresponds to the slope of the curves shown in Figure 3.8, if a double-log scale representation is chosen.

The signal flow graph shown in Figure 3.9 shows a simplified structure of a model which generates the product "trajectories" in the business field exhibited in Figure 3.7. Variables are again represented by nodes, cause and effect relations between the variables by arcs of the graph.

Basically, a model which describes the development of the total market and its growth rate and a production decision define trajectories in Figure 3.7. A production decision determines market share, if it is assumed that with the price given by eq. 3.6 all units can be sold. Unit price and average unit costs multiplied by the production quantity define sales, costs and profits. A further model is needed to relate investments and capital attributable to the product to production quantities. With given profits for the planning years and a discount rate, such quantities like DCF, ROI, ROC and the value of additional market share may be calculated.

Several authors have investigated extended models based on the same approach [27,54]. Formal portfolio selection models may be used to calculate optimal production decisions and investments if several products compete for scarce resources (viz. [79] and chapter 7). "What if?" sensitivity analysis and experimental designs may be employed to quantify risks which are more likely to be associated notably with "star" and "question mark" products [11].

Although the Boston Consulting Group approach is very simplistic and certainly not valid for many e.g. regulated markets and products it has its facination: the simple classification and some basic laws which are open to empirical falsification are employed to isolate important and understandable categories of data and variables.

Figure 3.8. Experience curves with deflated prices and costs

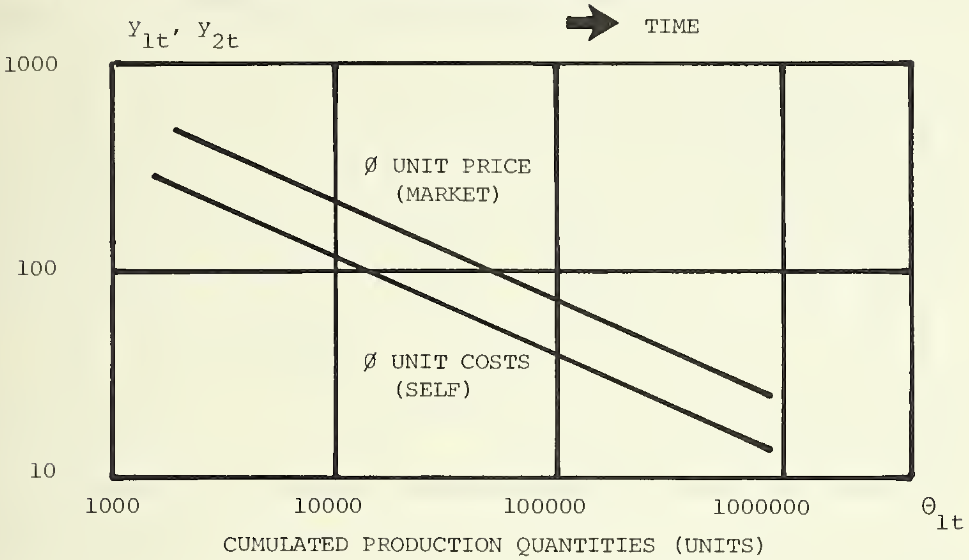


Figure 3.9. Flow graph business field planning models

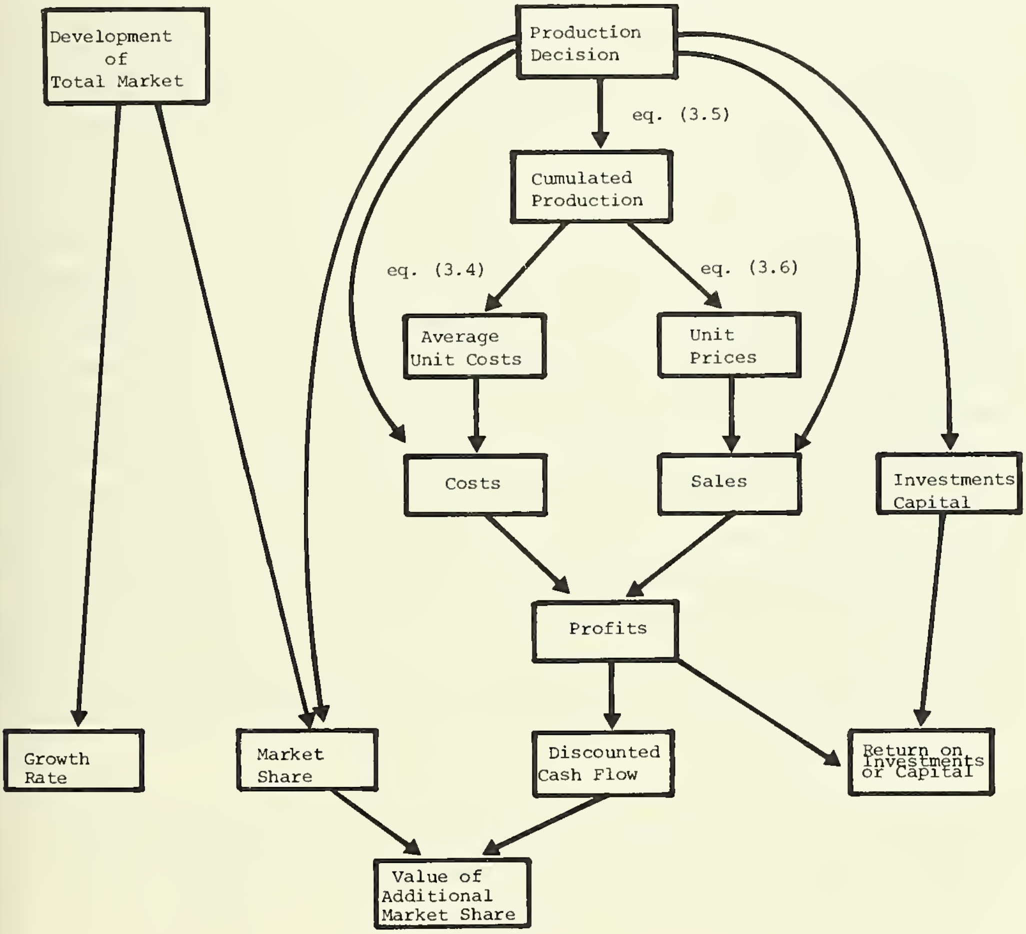
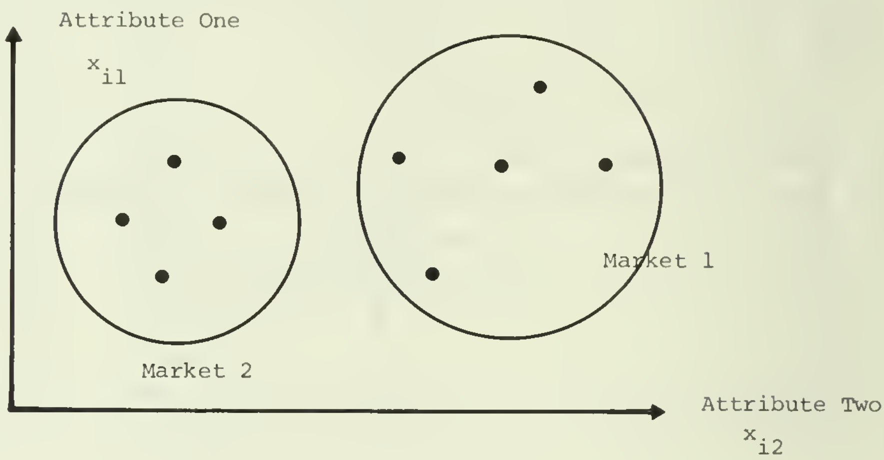


Figure 3.10. Market definition using multivariate analysis



PRODUCT POSITIONING USING ZIPF's LAW

Very often in nature and economics, it is observed that the size distribution of objects can be approximated by Zipf's law [81,39,64] which is described by

$$y_i = a_0 \cdot i^{a_1} \quad , \tag{3.7}$$

where y_i corresponds to the size of the object and i to its rank number. Figure 3.11 shows the graphical representation; Figure 3.12, a practical example using a double-log scale and market shares of products. The paramters of a_0 and a_1 may be estimated by simple regression. Several authors have dealt with the underlying statistical assumptions (viz. Hill [39] and ref.). In practice, one often observes deviations from the law notably for new introduced and "canabalizing" products. The law is of a static nature and does not take other variables, such as prices and advertising into consideration. It may, however, be used to roughly estimate the potential market share of a product which has not been introduced into the market. Since in this situation no historical data are available such information may be of great importance, notably to determine the introduction strategy.

It is assumed that the market share of the product will be close to the shares of products which, with respect to their attributes, most closely resemble it (for an extended model viz [4]). Figure 3.13 shows a transposed data matrix X^T for a soft drink container example [73].

MULTIVARIATE ANALYSIS [1,24,43,52,71,72]

Very often, model data may be represented in two dimensional tables or a data matrix $X = (x_{ij})$, where $i = [1,n]$ defines "objects" such as customers, markets, or products and $j = [1,m]$ "attributes" which describe properties of the objects. Frequently, values x_{ij} are obtained from surveys, discussions, and other subjective information. In other instances $j \equiv t$ and the x_{ij} represent measured time series values.

Multivariate analysis is understood as a collection of statistical techniques which allow the grouping and association of objects and attributes from given data matrices. It may be used for the classification and reduction of data and variables. Although the techniques are so far mainly used for marketing research purposes, they may also be employed to isolate important data and variables to be used with a corporate model.

In chapter 6, one of these techniques, namely multiple regression, will be discussed. Ideally, it allows the estimation of model parameters of an equation which describes a dependent variable as a function of several independent variables. It generates statistical quantities which allow one to distinguish between important and unimportant variables that may influence the dependent variable. An application example would be the isolation of important industry series influencing sales of a product or product group.

Techniques of multivariate analysis may also be used to identify important model variables, input data and parameters from a data analysis of model output data. Multiple regression and variance analysis are used for this purpose. Output data may be generated by so-called screening experimental designs (viz. Kleijnen [49], Rosenkranz, Bürgisser and Peter [63,65] and chapter 6).

Factor and cluster analysis together with scaling methods may be employed to define product groups and markets needed in a portfolio model as described above (viz. Figure 3.7 and 3.10). The application of Zipf's law for product positioning is another example for simple data classification to be used for modeling purposes.

Figure 3.11. Zipf's law

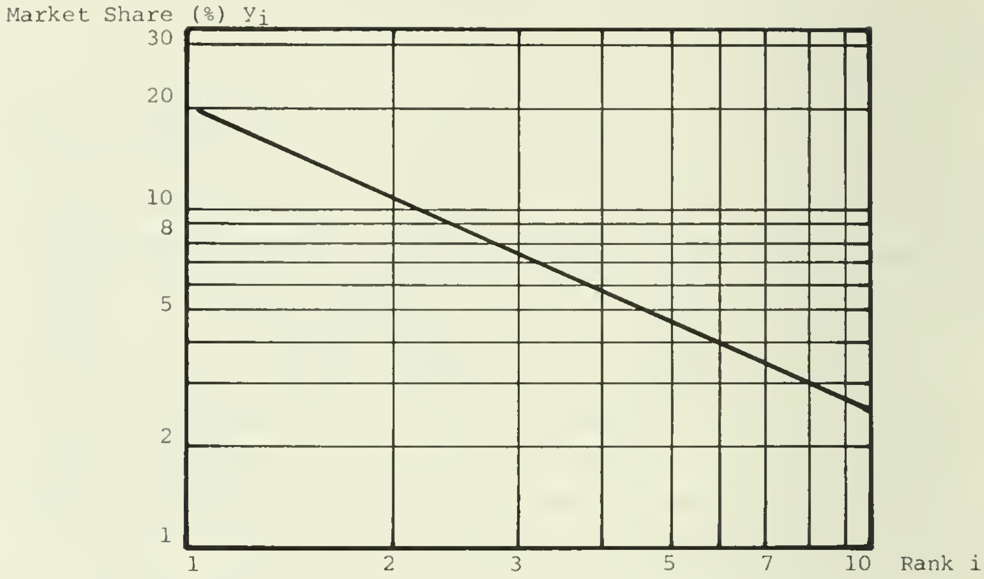
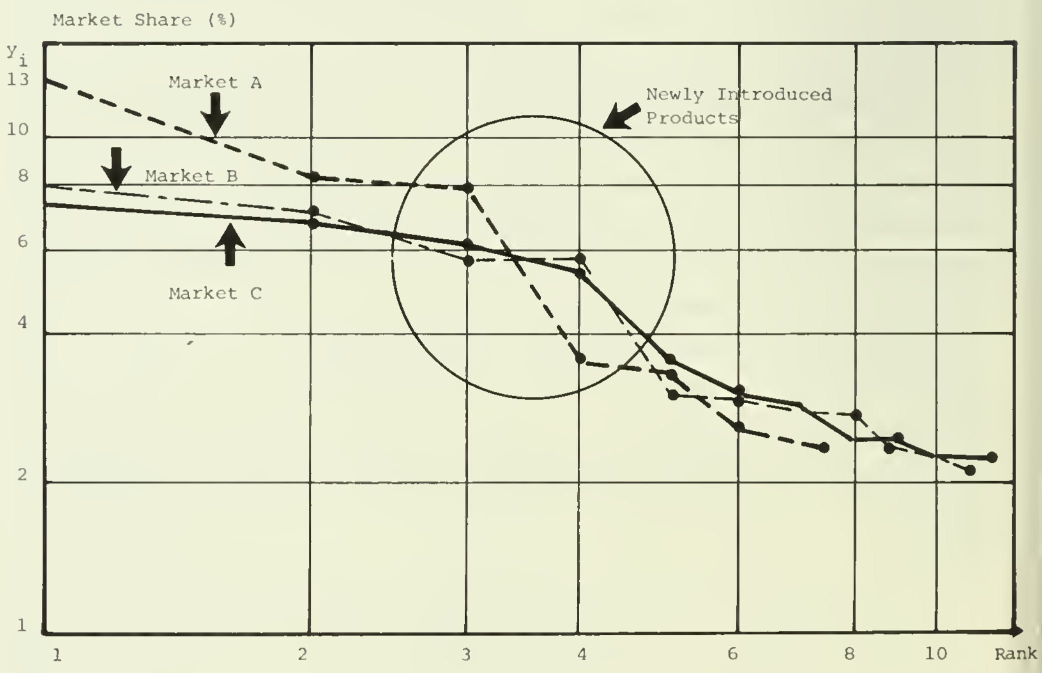


Figure 3.12. Examples for Zipf's law



The x_{ij} are defined and subjectively assessed on an interval scale between zero (unsatisfactory) and ten (very satisfactory). A variety of distance measures (viz. e.g. Späth [71, pp. 14-23]) may be used to express the similarity of the products. Also scaling methods may have to be used to transform the measurements of the attributes.

For the given example, the untransformed data and the distance functions

(3.8) $$L_{2i} = \sum_{j=1}^{m} (x_{0j} - x_{ij})^2$$

and

(3.9) $$L_{1i} = \sum_{j=1}^{m} \mid x_{0j} - x_{ij} \mid ,$$

where m = 14 and i = [1,5] are used to evaluate product similarities. One obtains $L_{21} = 31$; $L_{22} = 92$; $L_{11} = 18$ and $L_{12} = 30$. All other distances are larger. Using minimum distances, and Figure 3.12, one should expect a market share of more than ten percent for the new product.

Figure 3.13. Data matrix for positioning example

P R O P E R T Y			Own Product	COMPETITOR PRODUCTS				
			0	1	2	3	4	5
TRANSPORT	1	unbreakable	4	6	5	5	3	3
	2	light	6	8	3	6	4	2
	3	transparent	3	2	8	4	3	6
CUSTOMER	4	traditional	8	8	6	2	2	5
	5	reusable at home	5	6	2	3	5	2
	6	easily disposable	2	4	5	6	2	1
	7	chemically inactive	8	6	4	1	1	3
	8	heat resistant	4	3	3	1	1	2
PRODUCER	9	flexible form & color	1	3	2	4	8	6
	10	impermeable	10	10	8	5	5	2
	11	pressure resistant	4	5	4	2	2	5
	12	easily handled on existing equipment	6	7	6	1	4	8
SOCIETY	13	disposal	4	6	6	3	3	4
	14	recycling	6	7	3	4	1	7

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Equations

TYPES OF EQUATIONS

The system of equations represented by eq.([2.2-2.11) in chapter 2 relates endogenous, decision, and exogenous variables of the firm. From the classification of model variables, it is quite clear which varuables must be supplied as input to the model and which variables are determined within the model and supplied as output to the user.

In chapter 3, it was shown that in many instances it may be possible to gain further transparency regarding the model structure to achieve an increased effectiveness regarding the model solution whenever unidirectional cause and effect relations between model variables are expressed by the symbols used to denote different model variables.

Based on the same reasoning, it is advantageous to further distinguish different types of relations that appear in a corporate model. Such a classification can be effected from a number of different viewpoints. It seems that the three most important classifications are according to

- the origin and nature of a relation
- the functional form and the
- interpretation of the cause and effect relations expressed by it.

Every single classification is of importance with respect to the solution of a model as well as to its intended use. Only the first point will be dealt with in this chapter, whereas points two and three will be discussed in chapter 5.

In addition to eq. (2.2 - 2.11), it may also happen that relations connecting only model parameters have to be considered. Accordingly, one

should distinguish what in the literature is called a structural equation from a parameter equation or restriction. Since parameter equations or restrictions constrain the values of the objective function which is used for the parameter estimation of the structural equations, typically the Lagrange multiplier technique or nonlinear mathematical programming techniques become involved. Problems of this nature are briefly touched in chapter 6. They do not seem to be relevant for the solution and simulation step. The following classification of model equations is therefore based entirely on structural equations (eq. 2.1 - 2.11).

In analogy to a framework originally outlined by Tinbergen [19, pp. 13-16] for macroeconomic models, one may classify the structural equations of a corporate model into the following four categories:

1. behavioral relations
2. identities or definitions
3. technological or institutional relations
4. equilibrium relations or boundary conditions.

Tinbergen denotes the first three categories as "primary" relations and defines: "As a rule, the primary relations represent the direct logical ties between the variables introduced by economic behavior or by the logic of definition or technique [19, p.13]." Since the use made of an identity or definitional equation, the functional form of a technological relation or a boundary condition may be influenced by "economic behavior" within the firm or its environment, in a very wide sense all model equations could be called behavioral relations.[1] Accordingly, econometricians did not always draw sharp lines between these categories; especially identities and technological equations were often treated as a subclass of behavioral equations. However, throughout the following chapters a more restrictive definition will be used.

Behavioral relations express a hypothesis about economic behavior of the firm or its environment. All equations which explicitly contain decision variables or random variables will be treated as behavioral equations. A price-demand equation is a typical example. It expresses a hypothesis about the reaction of a market to a firm's price decisions. Behavioral relations are open to verification and validation.

In contrast to behavioral relations, the other two categories of model equations do not contain decision or random variables. They explicitly explain endogenous variables as a function of other endogenous, predetermined or exogenous variables.

Identities and definitional equations are most frequently met in the financial segment of a corporate model. An identity would e.g. equate total assets and total liabilities in the balance sheet of a firm. Simple examples for definitions are

$$\text{(4.1)} \qquad \text{REVENUE}_t = \text{SALES}_t - \text{COSTS}_t,$$

or

$$\text{(4.2)} \qquad \text{RENTABILITY}_t = \frac{\text{PROFITS}_t}{\text{LIABILITIES}_t} \quad .$$

but also definitional equations including lagged variables, such as the weighted moving average

$$\text{(4.3)} \qquad S_t = 0.6 \cdot S^*_t + 0.3 \cdot S^*_{t-1} + 0.1 \cdot S^*_{t-2} \ ; \ t \geq 2$$

could fall into the same category. In eq. (4.3) S^*_t would be a measured value.

Technological equations describe how various microeconomic production factors are combined in the production process of the firm to give a certain quantity of finished product or service which the firm supplies to its environment. This combination process is in general clearly influenced by management decisions. Classical cost- and production theory and its mathematical programming extensions, but also the organizational or behavioral theory of the firm, assume that the combination is accomplished in such a way that some goals of either optimization or satisfaction are attained (Eilon [5]). These goals to a very large extent prescribe the quantities of substitutional factors to be employed in production. The same is true with regard to limitational factors, because it is usually assumed that the firm only employs efficient factor combinations. Technological equations in a corporate model therefore do not contain decision variables. It is implicitly assumed that the goals of the firm are reached with the factor-combinations expressed by a technological relation.

A typical and simple example of a technological relation that is often used in practice may be expressed by the matrix equation

$$\text{(4.4)} \qquad \underline{q}_{rt} = W \cdot \underline{q}_{ft}$$

The equation relates a m-component vector of endogenous raw material quantities q_{rt} to a k-component vector of either endogenous or exogenous quantities q_{ft} of finished products via a m x k Walras-Leontief matrix of technological coefficients [4,11, p.38]. A similar equation could express quantities of finished products as a function of raw material quantities.

Technical coefficients that appear in these linear or even non-linear and simultaneous equations may be time dependent in which case they would be treated as exogenous variables. It is assumed that technological coefficients or parameters are defined outside the model by setting so-called technological or engineering variables. Relations that contain technological variables like pressure, temperature, speed, power and decision rules to determine these variables do not appear explicitly among the technological equations. This does not exclude that such relations, e.g. Gutenberg or engineering production functions (viz. Gutenberg [7], Chenery [2], Lücke [12, pp. 60-75], Krelle [11, pp. 41-54]) may be contained among the behavioral equations of a model.

Institutional relations like technological relations only relate endogenous and exogenous variables of a model. They describe relations between model variables that are set by the firm's environment. Expressions that describe sales and profit taxes or insurances the firm has to pay, are examples of institutional relations.

Equilibrium or boundary conditions restrict the values of endogenous variables in time and by value. An instantaneous equilibrium condition relates an endogenous variable at every state to other endogenous or exogenous variables. A typical short term or instantaneous equilibrium condition would be equation (4.5)

$$(4.5) \qquad I_t = \frac{1}{12} S_t$$

It states that a firm at every stage t (year) adjusts its inventory by value I_t in such a way that it is worth average monthly sales $\frac{1}{12} S_t$. A short term equilibrium condition represents a hypothesis or assumption about the development of certain model variables. Very often short term equilibrium conditions are used as a substitute for more complicated behavioral equations. One could say that short term equilibrium conditions frequently express a principle of "quasi-stationarity" [16].

This means that the rate of change to a disequilibrium between the endogenous variable explained and other variables contained in the

relation is small compared to all rates that lead to an equilibrium between the model variables.

A long range equilibrium condition like eq. (4.6) would in contrast restrict endogenous variables only over an infinite time horizon (viz. Mosbaeck-Wold [14, pp. 116-117]), e.g.

$$(4.6) \qquad \lim_{\substack{t\to\infty \\ k\geq 0}} \frac{1}{(t+1)} \cdot\cdot (I_k+I_{k+1}+\ldots+I_{k+t}) = \lim_{\substack{t\to\infty \\ k\geq 0}} \frac{1}{12(t+1)} \cdot (S_k+S_{k+1}+\ldots+S_{k+t})$$

As Wold states, these conditions do not represent assumptions about the model structure, but correspond to implications of the model structure. This may not be true in general, because one can imagine analytical model solutions in which model parameters are adjusted in such a way that a long range equilibrium condition is always fulfilled; but this would rarely be possible for parameter estimations and numeric model solutions.

Long range equilibrium conditions in a corporate model may be used to test a model's plausibility and stability by predictive testing. However, since the equations of such a model typically relate transient states of the variables, it is thought that the use of medium range equilibrium conditions like eq. (4.7) are more appropriate for this purpose:

$$(4.7) \qquad \frac{1}{m+1} (I_k+I_{k+1}+\ldots+I_{k+m}) = \frac{1}{12(m+1)} (S_k+S_{k+1}+\ldots+S_{k+m})$$
$$m,k\geq 0 \quad , \quad k+m\leq n$$

Medium range conditions may also contain lagged variables and possibly restrict the values of the endogenous variables in an estimation or solution of a model within its time horizon n.

Boundary conditions correspond to short or medium range equilibrium conditions with the difference that they are written as inequilities in the endogenous and exogenous state variables. Very often they appear as non-negativity constraints or constraints resulting from a linearization of a model (Tinbergen [19, p.16], Fels, Tintner [6,pp. 11-12]). They restrict the values of the endogenous variables in an estimation or solution only in the case that the strict equality in an inequality is approached. It is well known that such boundary conditions may be transformed into equations by an appropriate use of so-called slack or proxy variables.

Equations (4.8-4.9) show an example for such a transformation.

It is now assumed that yearly inventories by value are at least equal to the maximum of a given security level I_0 and the arithmetic mean of the average monthly sales of the current and two preceding years. The system of inequalities

$$(4.8) \qquad I_t \geq \frac{1}{36}(S_t + S_{t-1} + S_{t-2})$$

$$I_t \geq I_0$$

$$S_t \geq 0$$

may be transformed to a system of three non-linear equations in five unknowns

$$(4.9) \qquad I_t = \frac{1}{36}(S_t + S_{t-1} + S_{t-2}) + y_{1t}^2$$

$$I_t = I_0 + y_{2t}^2$$

$$S_t = y_{3t}^2$$

where the three slack variables y_{1t}, y_{2t} and y_{3t} are restricted to real values.[2] For the application of mathematical programming techniques, one would very often transform (4.8) into a system consisting of one equation and three non-negativity constraints:

$$(4.10) \qquad I_t^* \equiv (I_t - I_0) \geq 0$$

$$S_t \geq 0$$

$$y_{1t} \geq 0$$

$$I_t^* - \frac{1}{36}(S_t + S_{t-1} + S_{t-2}) + I_0 - y_{1t} = 0$$

In chapter 2, three reasons were given for including stochastic disturbances in a model equation. An equation containing stochastic disturbances will be treated as a behavioral equation.

The partition of model equations into basically two main groups that consist of the behavioral equations and the identities technological relations and equilibrium conditions has important practical consequences. Since the second group of equations is either deterministic by nature or definition, these equations may be used to substitute endogenous variables in the model. This is always possible if a formulation of the equations may be found which is explicit in different endogenous variables. With stochastic equations, variable substitution would be far more restricted.

The second group of equations very often does not pose any problems in the estimation, solution and validation step of the multi-step design procedure outlined in chapter 2 due to the fact that it does not contain any decision variables and stochastic disturbances. Experience with the CIBA-GEIGY models and survey results cited in chapter 1 indicate that some 80-95 percent of the structural equations of a corporate model usually belong to the second group.

FINANCIAL MODEL CASE STUDY

The methodology so far introduced to classify first, the type of question answered by a corporate model, second, the variables used and third, the types of equations employed in a corporate model is demonstrated with the following example financial model.

Assume that a firm consists of two companies A and B. Simplified versions of their budgeted balance sheets and income statements for the period 1978-1981 are shown in Figures 4.1 and 4.2, respectively. Company A is supposed to be the parent company, B a daughter company. Balance sheet and income statements are not consolidated. It may be seen from the balance sheets (*) that the parent company supplies a loan to the daughter company (Figure 4.1, line 5) and the daughter company (*) delivers products to the parent company (Figure 4.2, lines 18 and 21). From the income statement of the daughter company (*), one sees that ten monetary units of its yearly profits result from sales to the parent company and that five monetary units of its receivables result from deliveries to the parent company (line 9, Figure 4.1, line 3, Figure 4.2).

Figure 4.1. Balance Sheet and income statement parent company

BALANCE SHEET PARENT COMPANY (A)

Line		1978	1979	1980	1981
1	Liquid funds	80	90	100	110
	Receivables				
2	-third parties	160	200	240	280
3	-intercompany	0	0	0	0
4	Total receivables	160	200	240	280
5	Loan Daughter Company	20	20	20	20
6	Inventories	500	600	700	800
7	Total assets	760	910	1060	1210
	Short term liabilities				
8	-third parties	40	50	60	70
*9	-intercompany	5	5	5	5
10	Total short term liabilities	45	55	65	75
11	Long term liabilities	140	220	185	240
12	Loan parent company	0	0	0	0
13	Share capital	300	360	400	400
14	Reserves	160	160	260	360
15	Profits	115	115	150	135
16	Total liabilities	760	910	1060	1210

INCOME STATEMENT (A)

		1978	1978	1980	1981
	Sales				
17	-third parties	950	1000	1500	1700
18	-intercompany	0	0	0	0
19	Total sales	950	1000	1500	1700
	Variable costs				
20	-third parties	715	715	1130	1295
*21	-intercompany	20	20	20	20
22	Total variable costs	735	735	1150	1315
23	Variable expenses	100	150	200	250
24	Profits	115	115	150	135

Figure 4.2. Balance sheet and income statement daughter company

BALANCE SHEET DAUGHTER COMPANY (B)

Line		1978	1979	1980	1981
1	Liquid funds	20	30	40	50
	Receivables				
2	-third parties	5	5	5	5
*3	-intercompany	5	5	5	5
4	Total receivables	10	10	10	10
5	Loan daughter company	0	0 0	0	0
6	Inventories	50	75	100	130
7	Total assets	80	115	150	190
	Short term liabilities				
8	-third parties	10	35	60	80
9	-intercompany	0	0	0	0
10	Total short term liabilities	10	35	60	80
11	Long term liabilities	10	30	50	80
*12	Loan parent company	20	20	20	20
13	Share capital	0	0	0	0
14	Reserves	0	0	0	0
15	Profits	40	30	20	10
16	Total liabilities	80	115	150	190

INCOME STATEMENT (B)

		1978	1979	1980	1981
	Sales				
17	-third parties	80	130	180	230
*18	-intercompany	20	20	20	20
19	Total sales	100	150	200	250
	Variable costs				
20	-third parties	40	90	140	190
*21	-intercompany	10	10	10	10
22	Total variable costs	50	100	150	200
23	Variables expenses	10	20	30	40
24	Profits	40	30	20	10

MODEL STRUCTURE WITHOUT DECISION VARIABLES

The first type of user-question which may be answered by a corporate model is related to its behavior if no decision variables are contained in the model structure. In this instance the user has no possibility of interacting with the model by either setting target values for some endogenous variables or choosing the values of any decision variables. Indeed, the structural equations contain endogenous and exogenous variables only, furthermore the model contains behavioral equations only provided that stochastic disturbances have to be considered.

The consolidation of the balance sheet and income statements of companies A and B is very straightforward. In additicn, the example demonstrates the importance of tree calculations in corporate modeling.

Let XA_{it} denote the line variables of Figure 4.1 at time t and line number i, XB_{it} the corresponding variables of Figure 4.2, finally Y^{*}_{it} the consolidated variables of Figure 4.2. Since the consolidated variables only express the financial situation of the firm as an entity with respect to its environment, intercompany capital and product transfers have to be eliminated. After this calculation has been achieved, the results may directly be aggregated. It is important to note that the flow of calculations may also be reversed. The variables XA_{it} and XB_{it} are treated as exogenous or input variables, the endogenous variables Y^{*}_{it} are the output variables from the consolidation. While Figure 4.3 shows the result of the calculations, the arcs in the graph Figure 4.4 represent the cause and effect relations to be observed in the solution. The auxilliary endogenous variables YA_{it} and YB_{it} are used for the consolidation and are only introduced for notational reasons. For the simple example shown, no additional storage would have to be reserved for their calculation. A tree calculation may be used for the aggregation.

Figure 4.3. Consolidated balance sheet and income statement

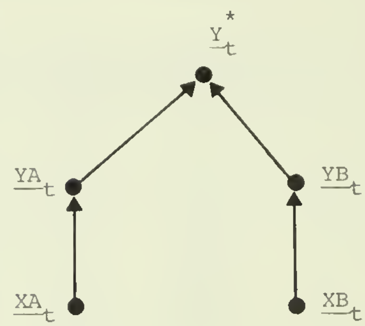
CONSOLIDATED BALANCE SHEET

Line		1978	1979	1980	1981
1	Liquid funds	100	120	140	160
	Receivables				
2	-third parties	165	205	245	285
3	-intercompany	0	0	0	0
4	Total receivables	165	205	245	285
5	Loan daughter company	0	0	0	0
6	Inventories	550	675	800	930
7	Total assets	815	1000	1185	1375
	Short term liabilities				
8	-third parties	50	85	120	150
9	-intercompany	0	0	0	0
10	Total short term liabilities	50	85	120	150
11	Long term liabilities	150	250	235	320
12	Loan parent company	0	0	0	0
13	Share capital	300	360	400	400
14	Reserves	160	160	260	360
15	Profits	155	145	170	145
16	Total liabilities	815	1000	1185	1375

CONSOLIDATED INCOME STATEMENT

		1978	1979	1980	1981
	Sales				
17	-third parties	1030	1130	1680	1930
18	-intercompany	0	0	0	0
19	Total sales	1030	1130	1680	1930
	Variable costs				
20	-third parties	765	815	1280	1495
21	-intercompany	0	0	0	0
22	Total variable costs	765	815	1280	1495
23	Variable expenses	110	170	230	290
24	Profits	155	145	170	145

Figure 4.4. Flow graph for model calculations



The structural equations of the model are formed by the system eq. 4.11 .

(4.11)

$$YA_{it} \equiv XA_{it} \quad ; \quad i = [1,24] \; ; \; i \notin (5,7,9,10,16,21,22)$$

$$YB_{it} \equiv XB_{it} \quad ; \quad i = [1,24] \; ; \; i \notin (3,4,7,12,16,18,19,20,21)$$

$$YA_{5t} \equiv YA_{9t} \equiv YA_{21t} \equiv YB_{3t} \equiv YB_{12t} \equiv YB_{18t} \equiv YB_{21t} = 0$$

$$YA_{7t} = XA_{7t} - XA_{5t}$$

$$YA_{10t} = XA_{10t} - XA_{9t}$$

$$YA_{16t} = XA_{16t} - XA_{9t}$$

$$YA_{22t} = XA_{22t} - XA_{21t}$$

$$YB_{4t} = XB_{4t} - XB_{3t}$$

$$YB_{7t} = XB_{7t} - XB_{3t}$$

$$YB_{16t} = XB_{16t} - XB_{12t}$$

$$YB_{19t} = XB_{19t} - XB_{18t}$$

$$YB_{20t} = XB_{20} - XB_{21t}$$

Only bookkeeping identities are used within the model.

"WHAT IF?" SIMULATION

Decision variables and behavioral equations appear in a model that is supposed to answer questions of the "What if?" type. The results of a simple deterministic "What if?" simulation is shown in Figure 4.5. As a starting point for the calculation, the values of the exogenous variables in Figure 4.2 were chosen. The simulation describes effects on the balance sheet and the income statement of company B provided that an exogenous ten percent yearly growth rate for sales is assumed. The system of equations 4.12 - 4.18 represents the structural equations of the model. For the sake of simplicity, simple and constant values have been assumed for the parameters and decision variables.

Exogenous Variables

$X\Delta_{it} = 0{,}1 \; ; \; i = (17{,}18)$	Absolute sales growth rate
$XI_{it} = 0{,}1 \; ; \; i = [1{,}4]$	Interest rate for liquid funds, short and long term liabilities, parent company loan
$\underline{XB}_t$	Variables and values of Figure 4.2

Decision Variables

$\Theta_{it} = 0{,}1$	Terms of payment($\hat{=}$ 36 days)
$\Theta_{2t} = 1{,}0$	Liquidity coefficient
$\Theta_{3t} = \Theta_{4t} = 0{,}5$	Relative fractions to finance
$\Theta_{5t} = \Theta_{6t} = 0$	Additional financial requirements; (3) liquid funds, (4) short term liabilities, (5) Long term liabilities, (6) parent company loan

Endogenous Variables

YF_t	Additional financial requirements
YLW_t	Short term liquidity variable without financing
YL_t	Short term liquidity ratio
$\underline{YB}_t$	Variables and values of Figure 4.5

Identities

(4.12)

$$YB_{4t} \equiv YB_{2t} + YB_{3t}$$

$$YB_{7t} \equiv YB_{1t} + YB_{4t} + YB_{5t} + YB_{6t}$$

$$YB_{10t} \equiv YB_{8t} + YB_{9t}$$

$$YB_{16t} \equiv YB_{10t} + YB_{11t} + YB_{12t} + YB_{13t} + YB_{14t} + YB_{15t}$$

$$YB_{19t} \equiv YB_{17t} + YB_{18t}$$

$$YB_{22t} \equiv YB_{20t} + YB_{21t}$$

$$YB_{24t} \equiv YB_{19t} - YB_{22t} - YB_{23t}$$

$$YL_t \equiv \frac{YLW_t}{YB_{10t}}$$

$$YB_{it} \equiv XB_{it} + X\Delta_{it} \; ; \quad i = (17,18)$$

$$YB_{it} \equiv XB_{it} \left(1 + \frac{X\Delta_{(i-3)t}}{XB_{(i-3)t}}\right) \; ; \quad i = (20,21)$$

Variable product costs increase with the same rate as sales.

$$YF_t \equiv (YB_{6t} - XB_{6t}) + (YB_{4t} - XB_{4t})$$

$$YB_{5t} \equiv YB_{9t} \equiv Y_{13t} \equiv Y_{14t} \equiv 0$$

Instantaneous Equilibrium Relations

(4.13) $$YB_{6t} = 0{,}5 \cdot YB_{19(t+1)} \qquad t < 1981$$

$$YB_{6(1981)} = XB_{6(1981)} \left[1 + \frac{(YB_{19(1981)} - XB_{19(1981)})}{XB_{19(1981)}}\right]$$

Inventories by value are set to a six month average of future sales.

Restrictions

(4.14) $$YB'_{it} \geq 0 \qquad i = [1,24]; \; i \neq (15,24]$$

Behavioral Equations

(4.15) $$YB_{it} = \Theta_{1t} \cdot YB_{i+15t} \qquad i = (2,3)$$

$$YB_{12t} = XB_{12t} + \Theta_{6t} \cdot YF_t$$

$$YB_{8t} = XB_{8t} + \Theta_{4t} \cdot YF_t$$

If all interests and a proportion Θ_{3t} of the additional financial requirements YF_t are paid in cash, the cash position would be

(4.16)
$$YLW_t = XB_{1t} + X\Delta_{17t} + X\Delta_{18t} - (YB_{20t} - XB_{20t}) - $$
$$- (YB_{21t} - XB_{21t}) - \{ \Theta_{3t} (1 + XI_{1t}) + $$
$$+ \Theta_{4t} \cdot XI_{2t} + \Theta_{5t} \cdot XI_{3t} + \Theta_{6t} \cdot XI_{4t} \} YF_t .$$

Provided that the liquidity coefficient Θ_{2t} is not endangered, short term financing is used as specified above.

(4.17) If $YL_t \geq \Theta_{2t}$
$$YB_{1t} = YLW_t$$
$$YB_{11t} = XB_{11t} + \Theta_{5t} \cdot YF_t$$
$$YB_{23t} = XB_{23t} + \{XI_{1t} \cdot \Theta_{3t} + XI_{2t} \cdot \Theta_{4t} + XI_{3t} \cdot \Theta_{5t} + $$
$$+ XI_{4t}\Theta_{6t} \} YF_t \quad .$$

In case the liquidity position is not good enough, the cash position is set in such a way that the liquidity condition is exactly fulfilled and all cash requirements are financed by long term liabilities:

(4.18) If $YL_t < \Theta_{2t}$
$$YB_{1t} = \Theta_{2t} \cdot YB_{10t}$$
$$YB_{23t} = XB_{23t} + \frac{1}{1-XI_{3t}} \cdot \{ - XI_{1t} \cdot (YB_{1t} - XB_{1t}) + $$
$$+ XI_{2t} \cdot (YB_{10t} - XB_{10t}) + XI_{3t} (\Theta_{3t} \cdot YF_t) + $$
$$+ \Theta_{5t} \cdot YF_t + (YB_{1t} - XB_{1t}) - (YB_{19t} - XB_{19t}) + $$
$$+ (YB_{22t} - XB_{22t}) + XI_{4t} (YB_{12t} - XB_{12t}) \}$$
$$YB_{11t} = XB_{11t} + (YB_{23t} - XB_{23t}) + \Theta_{3t} \cdot YF_t + \Theta_{5t} \cdot YF_t + $$
$$+ (YB_{1t} - XB_{1t}) - (YB_{19t} - XB_{19t}) + (YB_{22t} - XB_{22t})$$

The two last comparatively complex relations result from the consideration of the interest rates for long term liabilities in the same period as they are incurred (simultaneity).

The model consists mainly of linear algebraic equations. One simple homogeneous difference equation is used to relate inventories and future sales. State changes of the system are caused by the decision variables. Most changes are due to quantitative policies, however, since

the structure of some of the behavioral equations is influenced by the liquidity policy, the model also shows an example of what is usually called a qualitative policy (Tinbergen [19, p.3]). The model equations are completely recursive, i.e. by choosing an appropriate ordering of the equations, it is possible to solve the equations successively in an isolated fashion based on the values of the endogenous variables already calculated. This substitution process corresponds to what has been termed a tree calculation in chapter 3.

Figure 4.5. Results "What if?" simulation

"WHAT IF?" SIMULATION BALANCE SHEET DAUGHTER COMPANY (B)

Line		1978	1979	1980	1981
1	Liquid funds	21,4	42,0	71,0	95,25
	Receivables				
2	-third parties	8,8	14,3	19,8	25,30
3	-intercompany	2,2	2,2	2,2	2,20
4	Total receivables	11,0	16,5	22,0	27,50
5	Loan daughter company	0,0	0,0	0,0	0,00
6	Inventories	55,0	82,5	110,0	143,00
7	Total assets	87,4	141,0	203,0	265,75
	Short term liabilities				
8	-third parties	13,0	42,0	71,0	95,25
9	-intercompany	0,0	0,0	0,0	0,00
10	Total short term liabilities	13,0	42,0	71,0	95,25
11	Long term liabilities	10,0	45,0	89,0	138,50
12	Loan parent company	20,0	20,0	20,0	20,00
13	Share capital	0,0	0,0	0,0	0,00
14	Reserves	0,0	0,0	0,0	0,00
15	Profits	44,0	34,0	23,0	20,00
16	Total liabilities	87,4	141,0	203,0	265,75

INCOME STATEMENT (B)

		1978	1979	1980	1981
	Sales				
17	-third parties	88,0	143,0	198,0	253,0
18	-intercompany	22,0	22,0	22,0	22,0
19	Total sales	110,0	165,0	220,0	275,0
	Variable costs				
20	-third party	44,0	99,0	154,0	209,0
21	-intercompany	11,0	11,0	11,0	11,0
22	Total variable costs	55,0	110,0	165,0	220,0
23	Variable expenses	10,6	21,0	32,0	43,0
24	Profits	44,4	34,0	23,0	12,0

Already with the small and deterministic model shown, one has to pay attention to the correct ordering of the model-equations. In the following chapter, some algorithms are described which facilitate such an ordering also for bigger and more complex models.

Two further points are worth mentioning. First, in the example chosen, company B was viewed as an isolated segment; equations to link the daughter company to the parent company are missing. Second, the intended use of the model determines to a very large extent how the model variables and equations are classified. One could well imagine cases in which the sales increase or some of the interest rates are treated like decision variables, or, alternatively, that the relation between sales and receivables becomes an equilibrium equation, the relation between sales and inventories a behavioral equation.

"WHAT TO DO TO ACHIEVE?" QUESTIONS

A model that is intended to answer questions of the "What to do to achieve?" type possesses a structure with behavioral equations and decision variables. It has been indicated before that these questions are more restrictive than "What if?" questions, because the model user assigns target values to all or some endogenous variables and is interested in the values of the decision variables that lead to the predefined targets. Provided that the user defines as many target variables and values as there are degrees of freedom in the decision variables, the model possibly only has one single solution in the decision variables. In that case, all decision variables should be looked upon as endogenous variables with the consequence that actually the first type of question is answered. However, normally, there are a number of degrees of freedom left for the decision maker to interact with the model. Therefore, a "What to do to achieve?" question will, in most cases, also incorporate the properties of a "What if?" question. The following goal programming model (Charnes, Cooper, Ijiri [1], Ijiri [9], Salkin, Kornbluth [17], Eilon [5]) is intended to give an impression of such an application.

Assume that daughter company B with the basic solution of Figure 4.2 starts to produce two products in quantities ΘP_{1t} and ΘP_{2t}. The first product is sold to third parties, whereas the second product is supplied to the parent company. Assume further that sales to the market or deliveries to the parent company are not restricted by the demand on the

two products, but by the yearly capacities XC_{1t} and XC_{2t} of two plants of company B. Every product has to be processed first in plant number one and then in plant number two. In the first plant the yearly capacity is taken as $XC_{1t} = 4$ (capacity units/year) for all stages and one capacity unit is needed to produce one unit of product one or product two. For the second plant, one has $XC_{2t} = 6$ (capacity units/year). While it takes one capacity unit to produce one unit of produce two, it takes three capacity units to produce one unit of product one, i.e., if only product one were produced, its maximum yearly quantity would be two units in the second plant. Suppose that one unit of product one is sold for ten monetary units, while it costs five monetary units to produce it. The corresponding figures for product two are fifteen and five monetary units, respectively. It is assumed that both products are continuously substitutable, i.e. it is possible to produce all positive and real valued quantities that are compatible with the capacities.

Company B is assumed to possess a hierarchy of two goals. First, it wants to produce in such a way that the total variable profit of goods sold comes as close as possible to a budgeted target value of YT_t. Second, in the case that several equally good solutions exist with respect to the first goal, it wants to use as much of the available capacity of the second plant as possible.

The production submodel is characterized by the following variables and equations (eq. 4.19):

Exogenous Variables

$XC_{1t} = 4$	Yearly capacity of first plant
$XC_{2t} = 6$	Yearly capacity of second plant
$XP_{1t} = 10$	Sales price product one
$XP_{2t} = 15$	Sales price product two
$XK_{it} = 5$;	i = (1,2) variable unit costs for the products

Decision Variables

ΘP_{it} ;	i = (1,2) quantities of the two products produced

Endogenous Variables and Restrictions

$YT_t \geq 0$ Target variable: total variable profit of products sold

$YS_{i,t} \geq 0$; $i = (1,2)$ unused capacity of the two plants

$YD_t^+ \geq 0$ positive deviation from target profit

$YD_t^- \geq 0$ negative devision from target profit

$YC_{ijt} \geq 0$; $i = (1,2)$; $j = (1,2)$ capacities used by product number j in plant number i

$YCB_{it} \geq 0$; $i = (17,18)$ sales by value to third parties $(i = 17)$ and to the parent company $(i=18)$

$YCB_{it} \quad 0$; $i = (20,21)$ variable costs attributable to third parties $(i = 20)$ and to the parent company $(i = 21)$

Identities

(4.19) $$YS_{it} \equiv XC_{it} - YC_{i1t} - YC_{i2t} \qquad i = (1,2)$$

$$YT_t \equiv YD_t^- - YD_t^+ + (YCB_{17t} - YCB_{20t}) + (YCB_{18t} - YCB_{21t})$$

$$YD_t^+ \cdot YD_t^- \equiv 0$$

The last non-linear relation defines that one may not have both deviations different from zero at the same time.

Behavioral Equations

(4.20) $$YCB_{it} = XP_{(i-16)t} \cdot \Theta_{(i-16)t} \qquad i = (17,18)$$

$$YCB_{it} = XP_{(i-19)t} \cdot \Theta_{(i-19)t} \qquad i = (20,21)$$

$$(YC_{ijt}) = \begin{pmatrix} \Theta P_{1t} & \Theta P_{2t} \\ 3\Theta P_{1t} & \Theta P_{2t} \end{pmatrix}$$

This relation describes how much capacity is needed for different production levels.

The target values YT_t are given in the second line of Figure 4.6.

Figure 4.6. Target values and results for production submodel

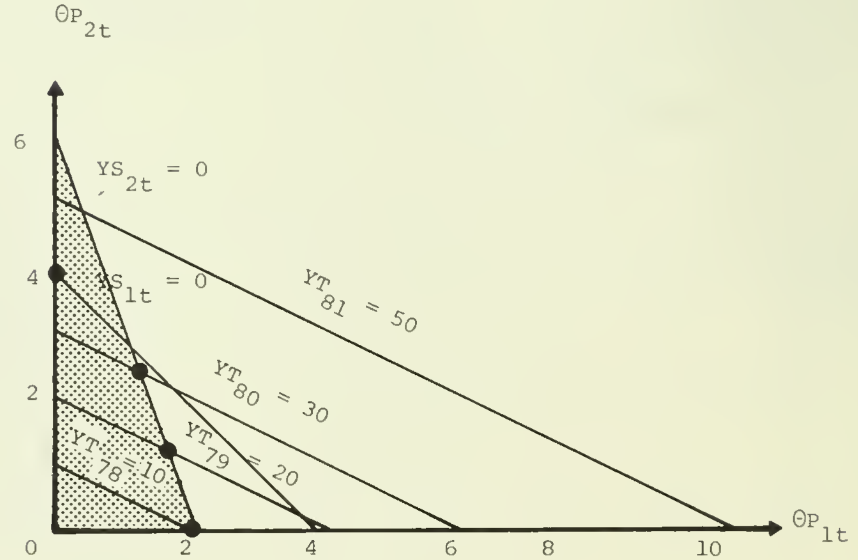
t	1978	1979	1980	1981
YT_t	10	20	30	50
ΘP_{1t}	2	1,6	1,2	0
ΘP_{2t}	0	1,2	2,4	4
YCB_{17t}	20	16	12	0
YCB_{18t}	0	18	36	60
YCB_{20t}	10	8	6	0
YCB_{21t}	0	6	12	20

A substitution of the behavioral equations. parameters and values of the exogenous variables into the identities given, leads to a more compact model formulation (eq. 4.21)

$$
\begin{aligned}
(4.21)\qquad & YS_{1t} = 4 - \Theta P_{1t} - \Theta P_{2t} \\
& YS_{2t} = 6 - 3\Theta P_{1t} - \Theta P_{2t} \\
& YT = 5\Theta P_{1t} + 10\Theta P_{2t} + YD_t^- - YD_t^+ \\
& YD_t^+ \cdot YD_t^- \equiv 0
\end{aligned}
$$

For $YD_{1t} = YS_{2t} = YD_t^- = YD_t^+ \equiv 0$ these equations are represented graphically in Figure 4.7

Figure 4.7. Graphical representation of goal programming model



The shaded region of Figure 4.7 indicates which combination of the decision variables are feasible. The combinations marked by a circle, represent the answers to the "What to do to achieve?" question provided that the following two decision rules are applied:

If $YD_t^+ \equiv YD_t^- \equiv 0$ let $YS_{2t} \equiv 0$

If YD_t^+ or $YD_t^- \neq 0$ choose the values of the decision variables that make the sum $(YD_t^+ + YD_t^-)$ as small as possible.

As may be seen, the first decision rule applies to the first three years, whereas in the last year the target value cannot be attained and YD_t^- becomes $YD_t^- = 10$.

The results of the graphical evaluation are given in Figure 4.6. In Figure 4.8 the sales and cost values of this solution were used as input to the "What if?" model described above. Additional sales and costs were financed as described before. In every period long term liability financing had to be used.

Several points should be noted in connection with the example described above. First, two goals were specified to determine uniquely the values of the two decision variables. With the goals given, no degree of freedom was left to the decision maker to set the values of the decision variables. If on the contrary only one, and this being the first, goal had been formulated, the decision maker could have chosen his decision from an infinite number of possible combinations for the years 1978 to 1981. In Figure 4.7, iso-profit lines have been drawn for all the planning years. Any point on their segments within the shaded region represents what usually is termed a feasible solution or answer. For the planning year 1981, the iso-profit line has no point in common with the shaded region. As a consequence, a feasible combination of the decision variables is chosen that is as close as possible to the iso-profit line for 1981. In the example chosen there is only one solution to this problem. In the other years, there would be an infinite number of solutions and the decision maker could arbitrarily chose the value of one decision variable in the shaded region.

Second, the example has been solved graphically. This kind of solution is out of the question for more complicated problems. However, the problem may be cast into a linear programming problem and solved numerically using linear programming software. This will be described in chapter 7.

Third, the structure of a model that answers questions of the "What to do to achieve?" type need not necessarily be linear and deterministic. The structural equations may also contain variables with leads and lags. Last, but not least, target values may be defined only for some stages or even only for the final stage of the time horizon of the model. Among the mathematical methods of operations research and management science there are a number of techniques available that may aid in the solution of these more general questions. Searching methods may be used in practically all circumstances. However, more problem oriented techniques like mathematical programming and non-classical variational methods may possess the advantage of far superior computing efficiency. Their disadvantage is often that they are not as flexible and versatile and not as easy to comprehend for a non-technical model user.

Figure 4.8. Results "What to do to achieve?" simulation

BALANCE SHEET DAUGHTER COMPANY (B)

Line		1978	1979	1980	1981
1	Liquid funds	32	63,5	95	106
	Receivables				
2	-third parties	10	14	19	23
3	-intercompany	2	4	6	8
4	Total receivables	12	18	25	31
5	Loan daughter company	0	0	0	0
6	Inventories	92	124	155	161
7	Total assets	136	205,5	275	298
	Short term liabilities				
8	-third parties	32	63,5	95	106
9	-intercompany	0	0	0	0
10	Total short term liabilities	32	63,5	95	106
11	Long term liabilities	38	75,0	114	123
12	Loan parent company	20	20	20	20
13	Share capital	0	0	0	0
14	Reserves	0	0	0	0
15	Profits	46	47	46	49
16	Total liabilities	136	205,5	275	298

Figure 4.8. (cont'd)

INCOME STATEMENT (B)

	1978	1979	1980	1981
Sales				
17 -third parties	100	146	192	230
18 -intercompany	20	38	56	80
19 Total sales	120	184	248	310
Variable costs				
20 -third parties	50	98	146	190
21 -intercompany	10	16	22	30
22 Total variable costs	60	114	168	220
23 Variable expenses	14	23	34	41
24 Profits	46	47	46	49

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FOOTNOTES TO CHAPTER 4

1. Non-economic behavior, activities, and goals described in a model are assumed to have economic effects.

2. The use of squared terms of the slack variables has the advantage that no non-negativity constraints have to be introduced with this notation.

Graphical Analysis and Representation

INTRODUCTION TO SIGNAL FLOW GRAPH REPRESENTATIONS

A corporate model consists of a system of equations that relate state and decision variables of the firm. Their interaction is assumed to by dynamic and is governed by the functional form of the equations.

As was stated previously, two of the main characteristics of corporate models are the large number of variables and equations which they have and their complexity. Usually the latter is to some extent due to the first. It was also mentioned that especially the financial segment of a corporate model may contain several thousand equations. Although these may have an extremely simple structure (e.g.linear identities), by their mere number they effect a loss of model-transparency on the user side. Apart from this, a model's complexity may arise from non-linearities and stochastic terms in model equations or the fact that the model may change its structure (qualitative policies) during its solution.

There exist numerous examples where under similar circumstances a graphical and two dimensional visualization of the model structure was found to be helpful in all stages of the modeling process [52, pp. 1-42]:

- Electrical and mechanical engineers visualize interactions of variables in normalized networks,
- Economists use signal flow graphs and a so called "path analysis" to represent cause and effect relations. Using some reduction rules it is possible to estimate a simple linear model with graph methods (viz. [64,60,51,30,31]).
- Programmers use flow charts to describe the flow of their interdependent calculations.

- Finally, some of the more successful management science methods, such as project planning methods [21,52,64,54,56 pp. 245-334], methods of transport and allocation planning [15,23,50] and decision tree analysis [40,38] owe a considerable part of their impact to the fact that it is possible to represent the problems graphically. In these cases the mathematical solution of the problem is based to a great extent on the graphical representations.

GRAPHICAL REPRESENTATIONS IN CORPORATE MODELING

Most corporate modelers intuitively understood the necessity to use graphical means to make the modeling clearer to oneself and others. Considing this goal and the fact that the structure of companies and the equation describing them have certain properties in common, it is surprising to note a great number of different kinds of graphical representations (viz. Schrieber [58]).

Beer [2] and Forrester [26,27] for example concentrate on the definitional phase of the modeling process and express qualitatively cause and effect relations between variables by directed arcs connecting nodes representing variables. However, it is worthwhile to note that with Forrester's standardized Industrial Dynamics (ID) networks one is already partially able to understand the underlying mathematical structure from the representation.

In the collection of pioneering essays on dynamic economic systems edited by Geyer and Oppelt [28] and more recent work on the same basis [57], standard control theory block diagrams were used. The number of standard graphical elements used for this kind of representation is much smaller than the number of elements used in an ID network.

SIGNAL FLOW GRAPHS

Figures 3.3 and 3.9 contain examples for simple flow graph representations. Essentially two generic or graphical elements are used: nodes and arcs. A linear graph G = (X,U) is defined as a collection of nodes X and arcs U which connect these nodes (viz. [4,8,9,34,50,55,56]). Arcs do not touch except in nodes. However, this may not be possible in a two dimensional representation. "Intersecting" arcs do not define nodes at the intersection. Nodes x_i, x_j, x_k, εX represent model variables, constants or

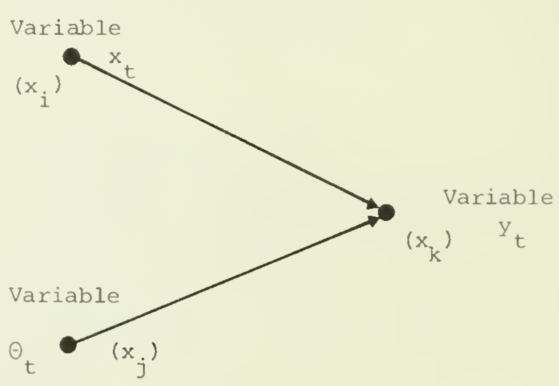
"inhomogeneities" in a model. Directed arcs correspond to cause and effect relations between variables and constants[1]. They are denoted by $\{x_i, x_j,\} \epsilon U$ where x_i is the origin and x_j the terminal node of an arc. Node x_j is also called the follower of node x_i; node x_i is the predecessor of node x_j.

Nodes which have only nodes incident from them are called sources. They represent variables (or constants) which may influence other variables, but which are determined outside of a model. Nodes which have only nodes incident on them are sinks. The corresponding endogenous variables do not influence other variables. A graph possessing only nodes with at least one arc incident on or incident from it is called a connected graph. In a connected graph two arbitrary nodes x_i, x_j, ϵX may either be connected by a so called path or by a so called chain. A path is a sequence of directed arcs in which one or more of the arcs is traversed opposite to its direction, in a chain arcs are only traversed in their direction.

If the graph representing a model is not connected, then the model consists of at least two isolated submodels.

Every arc is incident from one and only one node as shown in Figure 5.1. The graph represents a model relation in which an endogenous variable y_t, represented by node x_k, is influenced and explained by an exogenous variable x_t (node x_i) and a decision variable Θ_t (node x_j). Symbols to denote exogenous variables always have a time index and should not be mixed up with the symbols used for a node. In the paragraphs which follow, however, the symbols used to denote variables will also be employed to denote the nodes.

Figure 5.1. Signal flow graph representation



Note the following restrictions which follow from the above definitions:

- Since every arc is incident from exactly one node,all causes (origin or beginning node of an arc) and effects (terminal nodes of the arcs) in a model are exactly identified.
- Every variable may be represented by only one node. This means that the model structure may not contain two or more relations which explain the same variable. The representation does not allow for overdetermined model structure.

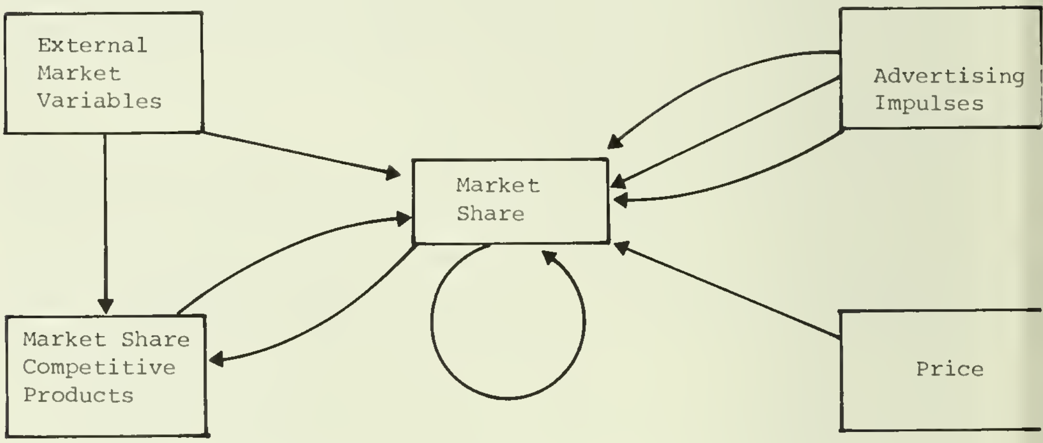
Some additional observations should be made:

- Exogenous, stochastic and decision variables are usually represented by sources. These variables are determined outside of a model. There are no cause and effect relations which define or explain them.
- Endogenous variables must be represented by nodes which have at least one arc incident on them. In other words: every endogenous variable must be explained by one model equation or relation. In Figure 5.1 y_t is an endogenous left hand side variable, whereas x_t and Θ_t are right hand side variables in an equation.
- Endogenous variables may influence themselves, e.g. if a new value of a variable is influenced by previous values of the variable. Such a cause and effect relation is represented by an arc which starts and terminates in the same node. This type of arc will be called a self-loop in the sequel.
- Endogenous variables may influence other endogenous variables which may again influence the original variable. This is represented by a sequence or chain of arcs which start and terminate in the same node. Such a chain will be called a cycle or loop. A loop or self-loop in a signal flow graph indicates logically a feed-back or feed-forward relation.
- Several unidirectional arcs between two nodes represent different types of cause and effect relations. This may e.g. be the case if a variable influences another variable with different leads and/or time lags.

Figure 5.2 represents a simple marketing model which expresses relations as they have been described. The market share of a product in a certain period is explained by its previous value, advertising impulses with different time lags, product price, external market variables, and the market share of competitive products. Note that a second model relation

would describe the development of the market share of the competitive products as a function of the external market variables and, by a feedback relation, by the market share of the own product.

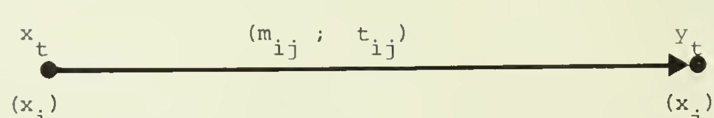
Figure 5.2. Flow graph marketing example



GENERALIZED SIGNAL FLOW GRAPHS (GESIFLOG)

Additional information concerning the form of model equations is obtained from the graphical representation if a vector of so called arc transmittances m_{ij} and time-shifts t_{ij} is defined on every arc $\{x_i, x_j\}$ between two nodes x_i and x_j (viz. Figure 5.3). The real valued transmittance m_{ij} causes a proportional transformation of the input variable of "signal" x_t represented by node x_i.

Figure 5.3. Generalized signal flow graph



The integer valued time shift t_{ij} for $t_{ij} < 0$ effects a lag, for $t_{ij} > 0$ a lead of variable x_t with respect to variable y_t. As a result of the definitions of m_{ij} and t_{ij}, variable x_t is shifted by t_{ij} time units and multiplied by m_{ij}. It influences the endogenous variable y_t according to

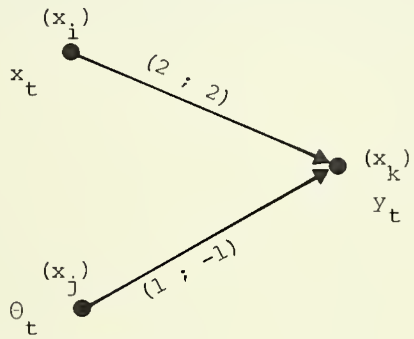
(5.1) $$y_t \sim m_{ij} \cdot x_{(t+t_{ij})} \quad .$$

For Figure 5.3 one would have an exact equality, because x_t is the only cause for changes in y_t.

In general, however, one has more than one variable influencing an endogenous variable, or more than one arc incident on the node representing it. In its simplest form a GESIFLOG only represents conjunctive relations (viz. e.g. [20,21,55,56]). All cause and effect relations represented by arcs unconditionally at all times influence the variable represented by the terminal node. The effects from different original variables are added up and equated to the endogenous variable. Figure 5.4 is a representation of the equation

(5.2) $$y_t = 2\, x_{t+2} + \Theta_{t-1} \quad .$$

Figure 5.4. Representation of an equation



Generally one has an equation

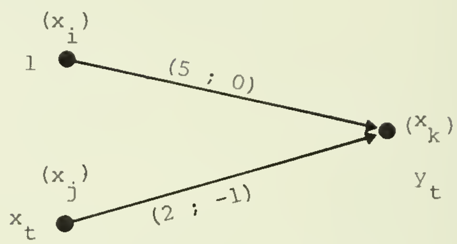
(5.3) $$y_{it} = \sum_j m_{ij}\, x_{i(t+t_{ij})}$$

for every node of the graph which has arcs incident on it. Note that in eq. (5.3) right hand side variables are denoted as exogenous variables. They could also be other endogenous variables, decision variables, stochastic variables or constants. In the last case a node designated by "1" is introduced. The constant itself would define a transmittance, the time

shift t_{ij} would be $t_{ij} = 0$. Figure 5.5 is a representation of the equation

(5.4) $$y_t = 2\,x_{t-1} + 5 \quad .$$

Figure 5.5. Representation of a constant



Since a GESIFLOG is a representation of equations, one may infer that the total number of equations in a model is equal to the number of nodes in the GESIFLOG which have arcs incident on them. This may also be seen from the following example.

REPRESENTATION OF AN INVENTORY MODEL

The following deterministic inventory model may be used for a further illustration. It is self explanatory and consists of the following variables, initial conditions, relations and parameters.

Endogenous Variables

y_{1t} , y_{10}	inventory level at time t and its initial value
y_{2t} , y_{20}.	order backlog, initial value
y_{3t} , y_{30}	incoming orders in period [t-1, t], initial value
y_{4t} , y_{40}	accumulated profits, initial value

Decision Variables

Θ_t	quantity ordered in period [t-1, t]

Relations

Inventory.

(5.5) $$y_{1t} = y_{1(t-1)} + \Theta_t - \frac{b}{a} \cdot y_{2t}$$

Order Backlog.

(5.6) $$y_{2t} = y_{2(t-1)} + y_{3t} - \frac{1}{a} \cdot y_{2t}$$

Incoming Orders.

(5.7) $$y_{3t} = y_{3(t-1)} + d \cdot (y_{3\infty} - y_{3t})$$

Profits.

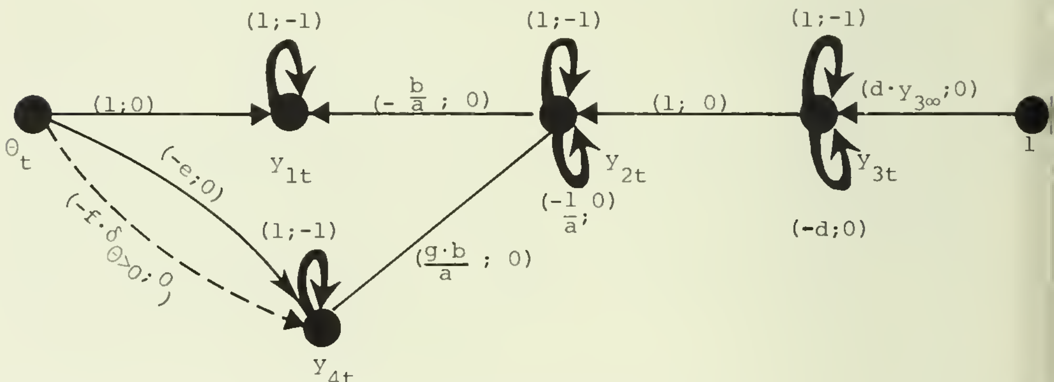
(5.8) $$y_{4t} = y_{4(t-1)} + \frac{g \cdot b}{a} \cdot y_{2t} - f \cdot \delta_{\Theta>0} - e \cdot \Theta_t$$

Parameters

a	exponential delay [26, p. 86-92] between order backlog and inventory depletion
b	average quantity per order
$y_{3\infty}$	saturation level of orders
d	order increase rate
e	price of goods ordered
f	fixed charge of an order
g	price of goods sold
$\delta_{\Theta>0}$	unit step function, i.e. $\delta = 0$ for $\Theta_t = 0$, $\delta = 1$ for $\Theta_t \neq 0$.

Figure 5.6 is a representation of equations (5.5 - 5.8). Note that eq. (5.8) contains a non-conjunctive term $f \cdot \delta_{\Theta>0}$ which is conditional on the order quantity Θ_t. This shows a first limitation of GESIFLOG representation, since a variable and function must be indicated on an arc. A different type of arc has been introduced in Figure 5.6 to account for this exception.

Figure 5.6. GESIFLO graph for sales-inventory system



ADVANTAGES AND DISADVANTAGES OF GESIFLO REPRESENTATION

Generalized signal flow graphs, as described thus far, represent models which consist of deterministic linear either algebraic or difference equations.

Since most equations in a corporate model, notably in the areas of finance and production, seem to possess this type of structure, a GESIFLOG allows their complete representation. As will be shown below, it may further serve for a simplification or even mathematical solution of the model or parts of it.

It will be seen that the graph structure allows the formulation of simple algorithms by which the equations of a model may be checked for a correct time sequence of the variables. Also a decomposition of a total model into simultaneous and recursive submodels may be carried out by algorithms based on the GESIFLOG representation (viz. appendix chapter 5).

However, stochastic, non-conjunctive or nonlinear model equations to some extent conflict with the linear representation. Either simplifications are made in these cases or new generic elements and notations are introduced into the graphical representation.

The following sections serve several purposes: First, the advantages of the linear representation are demonstrated using simple examples which are relevant for corporate modeling applications. Second, proposals will be made for the extension of the linear, deterministic representation. Third, several algorithms are described which may be used to support a computer based model construction and solution.

LINEAR ALGEBRAIC SYSTEMS AND EXAMPLES FOR REDUCTION RULES

For a system of linear algebraic equations one has $t_{ij} = 0$; $x_i, x_j \varepsilon X$ and the GESIFLO notation may be further simplified by dropping the second vector component altogether from it. By doing this one arrives at the traditional signal flow graph representation as it is due to Shannon and Mason.

One sees at once that it is possible to represent systems of linear algebraic equations by a graph. The nodes correspond to the variables and inhomogeneities, the transmittances correspond to the coefficients of the variables.

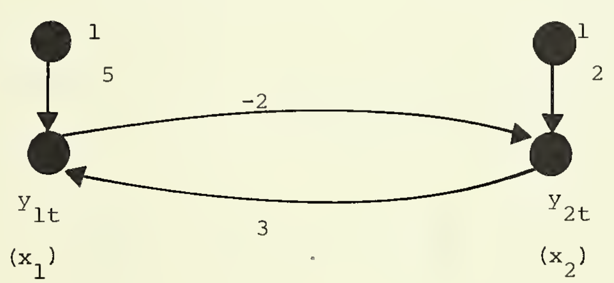
For example the system

(5.9) $$2\,y_{1t} + y_{2t} = 2$$

$$y_{1t} - 3y_{2t} = 5$$

corresponds to the graph shown in Figure 5.7[2].

Figure 5.7. Flow graph of eq. 5.9



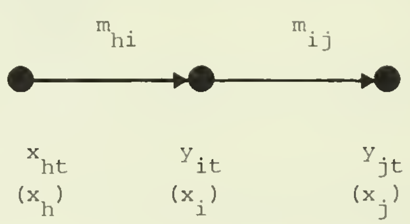
If one solves a system of simultaneous equations like (5.9) numerically then the iterations normally correspond to a stepwise elimination process of the variables. In a solution a variable is either expressed as a function of other variables or the inhomogeneities of the system. One can show by basically using three simple rules and their generalization that it is possible to perform the same calculations directly in a signal flow graph.

It can be seen that a graph reduction consisting of an elimination of arcs and nodes corresponds to the elimination of variables (viz. e.g. [9, 21,37,39,41,42]). The rules are

Reduction For Arcs In Series

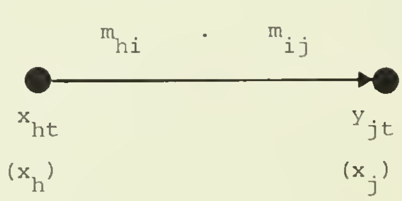
Consider the so called cascade arcs in Figure 5.8.

Figure 5.8. Arcs in series



From eq. (5.3) one has $y_{it} = m_{hi} \cdot x_{ht}$ and $y_{jt} = m_{ij} \cdot y_{it}$. Substitution of y_{it} leads to $y_{jt} = m_{hi} \cdot m_{ij} \cdot x_{ht}$ and the representation of Figure 5.9

Figure 5.9. Reduction of cascade arcs

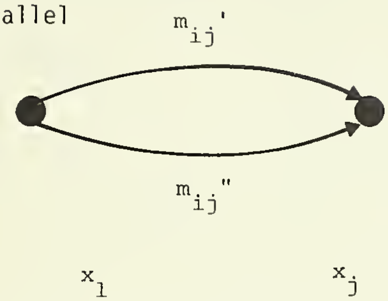


It follows that the transmittance of a chain of cascade arcs corresponds to the product of the transmittance of the arcs in the chain.

Reduction For Arcs In Parallel

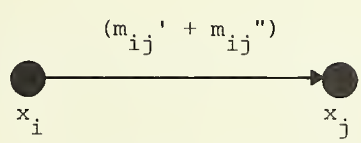
Consider the graph of Figure 5.10:

Figure 5.10. Arcs in parallel



Applying eq. (5.3), it follows that $y_{jt} = (m_{ij}' + m_{ij}'') \cdot x_{it}$. The reduced graph is shown in Figure 5.11.

Figure 5.11. Reduction of arcs in parallel

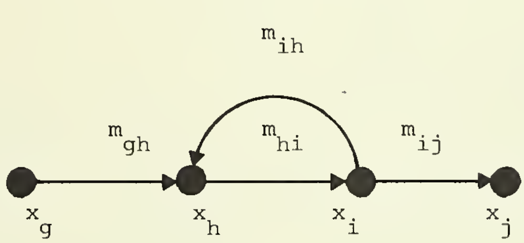


It follows that the transmittance of a chain of arcs in parallel corresponds to the sum of the transmittances of the parallel arcs.

Reduction Of Feedback- And Self-Loops

Consider the graph in Figure 5.12.

Figure 5.12. Signal flow graph with feedback loop



The arcs $\{x_h, x_i\}$, $\{x_i, x_h\}$ form a loop.
According to eqs. (5.3) one obtains the three equations

$$y_{ht} = m_{gh} \cdot x_{gt} + m_{ih} \cdot y_{it}$$

$$(5.10) \qquad y_{it} = m_{hi} \cdot y_{ht}$$

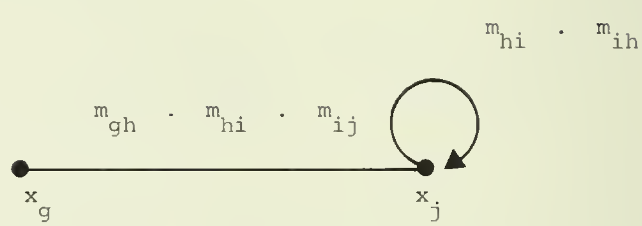
$$y_{jt} = m_{ij} \cdot y_{it} \, .$$

Elimination of y_{ht} and y_{it} leads to

$$(5.11) \qquad y_{it} = m_{gh} \cdot m_{hi} \cdot m_{ij} \cdot x_{gt} + m_{hi} \cdot m_{ih} \cdot y_{jt}$$

and the graph of Figure (5.13) with a self-loop.

Figure 5.13. Graph with self-loop

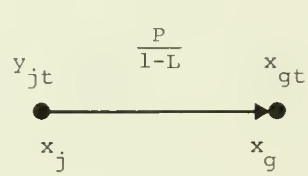


This can be further reduced to

$$(5.12) \qquad y_{jt} = \frac{P \cdot x_{gt}}{1-L} = \frac{m_{gh} \cdot m_{hi} \cdot m_{ij}}{1-m_{hi} \cdot m_{ih}} \cdot x_{gt},$$

and one obtains ultimately the graph of Figure 5.14:

Figure 5.14. Reduction of feed-back-loop



One calls P the forward chain transmittance, L the loop transmittance [39].

By applying eq. (5.3) one can easily carry out a similar reduction if several chains between sources and sinks touch a feedback- or self-loop.

Touching Loops And Mason's Formula

In the case that different loops of a signal flow graph have several arcs and nodes in common, one may commit errors in the reduction process if one only applies the rules so far discussed.

Loops are said to be touching if they have either an arc or a node in common.

For these cases Mason [41,42,9,66] has developed a reduction formula which is a generalization of the results so far derived. The formula is often easy to apply and corresponds to the solution of a simultaneous linear system of equations by Cramer's rule [9, p. 140-216] with the advantages and disadvantages of the latter.

If x_j denotes an arbitrary sink and x_i an arbitrary source in the graph, Mason showed that the value of a variable represented by x_i is transformed into the value of the variable y_{jt} represented by x_j by the formula

$$(5.14) \qquad y_{jt} = [(1/D)\sum_k P_h D_h] \cdot x_{it}$$

In eq. (5.14) D is the so called graph determinant defined by

$$(5.15) \qquad D = 1 - \sum L_m + \sum_{\substack{m,n \\ n \neq m}} L_m L_n - \sum_{\substack{\ell,m,n \\ \ell \neq m,n \\ m \neq n}} L_\ell \cdot L_m \cdot L_n + - \ldots \quad .$$

The determinant is calculated using the loop transmittances L_m defined above. The second term in eq. (5.15) corresponds to the sum of all loop transmittances in the graph. The third and fourth terms represent the sum of transmittance-doublets $L_m \cdot L_n$ and of triplets $L_\ell L_m L_n$, respectively, of nontouching loops in the graph. The number of terms with alternating signs in (5.15) corresponds to the highest multiplet that can be found in

the graph plus one for the constant term in (5.15).

P_h denotes a forward transmittance of a chain between x_i and x_j; D_h is the determinant of the graph that remains if all arcs and nodes contained in the chain denoted by h are removed from the original graph.

In eq. (5.14) the summation extends over all possible chains between x_i and x_j . The equation holds in all cases , but becomes less and less manageable if the number of nodes and the "connectedness" of the graph increase. Like Cramer's rule or one of the revised methods for pivoting in linear programming, an application of Mason's formula is primarily interestingin cases where the corresponding matrix of coefficients M of the algebraic system is sparse, e.g. contains a great proportion of zero elements.

For strongly connected and large graphs one should resort to standard matrix inversion techniques, and to the computer. The reason for this conclusion is easy to understand: either one searches for all chains between a source and a sink in the graph as well as for all loops in a non-systematic way and thereby easily commits errors, or one applies algorithms based on graph theory, for instance by Ford [23,24] and Roy [54,56], and loses all advantages of a hand calculation and reduction.

If a strongly connected and large graph is used for visualization purposes only, it may be reduced symbolically by using the matrix vectors, $\underline{Y}_t = M^{-1} \cdot \underline{X}_t$ provided that M has full rank and the vectors $\underline{Y}_t$ and $\underline{X}_t$ denote the output and input variables, respectively.

The advantages of applying the reduction rules described so far, are best demonstrated using examples which are of practical relevance in corporate model building. The algorithms described in the appendix to this chapter may support the reduction process.

STATIONARY AND ACYCLICAL PARTS REQUIREMENT PROBLEM

In many industrial applications one is asked to calculate the requirements of intermediate and raw products to produce a given quantity of an end product. This information is frequently needed for cost accounting purposes as well as for inventory, production and capacity planning problems. As such, the problem is clearly a dynamic one. Production and change-over times within the production-stages lead frequently to a lag-structure in the equations that describe the process, and thus stationary as well as nonstationary solutions to such a model can be of great

interest [52]. Sometimes one has to use stochastic models, since either demand for end products or change-over and production times are random variables (e.g. [13]).

In the following we only deal with a version of these models that may be expressed by linear algebraic equations. The models are deterministic, have only stationary solutions and possess no lag structure. The latter may be assumed in case that the time base of the model is large compared to production and change-over times. The formulation of this kind of model dates back to Vaszonyi [63,46].

The example model consists of the following state variables and parameters:

Exogenous Variables

x_{1t}	Demand for end products
x_{2t}	

Endogenous Variables

y_{3t}	Required intermediate products
y_{4t}	
y_{5t}	
y_{6t}	Required quantities of raw products
y_{7t}	

Parameters

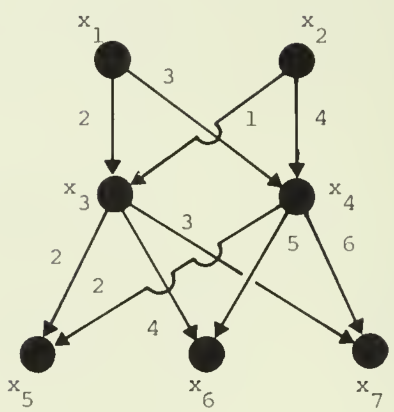
a_{ij}	Required quantity of intermediate product i to produce one unit of end product j ($i = 3,4$; $j = 1,2$)
b_{ij}	Required quantity of raw product i to produce one unit of intermediate product j ($i = 5,6,7$; $j = 3,4$)

If the parameters attain the values shown in the matrices A and B below, one obtains the signal flow graph shown in Figure 5.15.

(5.16) $$A = (a_{ij}) = \begin{pmatrix} 2 & 1 \\ 3 & 4 \end{pmatrix}, \quad i = 3,4;\ j = 1,2$$

(5.17) $$B = (b_{ij}) = \begin{pmatrix} 2 & 2 \\ 4 & 5 \\ 3 & 6 \end{pmatrix}, \quad i = 5,6,7;\ j = 3,4$$

Figure 5.15. Signal flow graph for parts requirement problem



The (7 x 7) matrix M of transmittances for the example shown in Figure 5.15 is a triangular matrix and may be written as a block matrix[3].

(5.18) $$M = (m_{ij}) = \left(\begin{array}{c:c:c} N_1 & N_1 & N_2 \\ \hdashline A & N_1 & N_2 \\ \hdashline N_2' & B & N_3 \end{array}\right), \quad \begin{array}{l} i = [1,7] \\ j = [1,7] \end{array}$$

The matrices N_i, i = 1,2,3 are zero-matrices of dimension (2 x 2), (2 x 3) and (3 x 3) respectively.

Using the rules for graph reduction of arcs in series and arcs in parallel one directly obtains

(5.19) $$y_{5t} = (2 \cdot 3 + 2 \cdot 2) \cdot x_{1t} ,$$

so that one would need $y_{5t} = 1000$ units to produce $x_{1t} = 100$ units.

It is interesting to observe that the representations of a signal flow graph and the calculations connected with it can often be simplified considerably if one uses vector and matrix notation with greater numbers of equally structured equations.

For example if one defines a vector $\underline{Y}_t$ with

$$\underline{Y}_t = \begin{pmatrix} y_{5t} \\ y_{6t} \\ y_{7t} \end{pmatrix} \tag{5.20}$$

as output and a vector $\underline{X}_t$ with

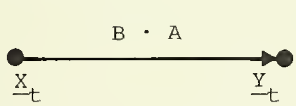
$$\underline{X}_t = \begin{pmatrix} x_{1t} \\ x_{2t} \end{pmatrix} \tag{5.21}$$

as input variable, one sees immediately for the special case discussed here that one obtains the matrix product B . A as a matrix of transmittances

$$\underline{Y}_t = B \cdot A \cdot \underline{X}_t \; . \tag{5.22}$$

In the case that one is only interested in how many units of the raw products are needed for a given demand for end products, the graphical representation is reduced to Figure 5.16.

Figure 5.16. Reduced flow graph

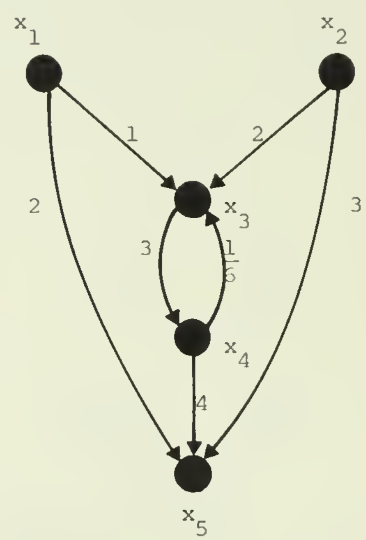


STATIONARY AND CYCLICAL PARTS REQUIREMENT PROBLEM [45,52 pp.224-238]

Consider the flow graph shown in Figure 5.17. One raw product represented by x_5 is directly mixed with intermediate product number three and at the same time is transformed into intermediate product number four. (Signal flow is opposed to material flow!) A part of the quantity of intermediate product number three produced is fed back into the preceeding production stage. The transmittances of the arcs have the same meaning as in

the problem discussed above.

Figure 5.17. Cyclical parts requirement problem



Cyclical problems are quite often important in the chemical industry (i.e. distillation processes). In the graph the feedback may be seen from the loop between nodes x_3 and x_4. If one wants to express y_{5t} as a function of x_{1t} and x_{2t} this can easily be achieved by an application of the reduction rules discussed before. In accordance with Figure 5.14 the loop has to be reduced using eq. (5.13). One obtains

$$(5.23) \qquad y_{5t} = \left(\frac{P_1}{1-L} + P_2 ; \frac{P_3}{1-L} + P_4 \right) \cdot \begin{pmatrix} x_{1t} \\ x_{2t} \end{pmatrix} ,$$

and with the given transmittances one has

$$(5.24) \qquad y_{5t} = M \cdot \begin{pmatrix} x_{1t} \\ x_{2t} \end{pmatrix} = (26;51) \cdot \begin{pmatrix} x_{1t} \\ x_{2t} \end{pmatrix} .$$

It should be stressed that the solution of the problem holds regardless of the values of the transmittances, as long as they remain positive in the reduced form of eq. (5.23). The equation which is nonlinear in the original transmittances may be used in a deterministic simulation of the input variables or in a stochastic simulation if the transmittances have to be considered as random variables.

TRANSFER PRICES

Touching loops are encountered in the following example: Consider an international company that produces in several countries. The national companies are organized independently, that is to say, they decide themselves what they buy and sell. It is assumed that they exchange intermediate products. The production of the latter is locally connected with variable and fixed costs. If the quantities of intermediate products produced and exchanged as well as local fixed and variable costs are known, the question arises of how the products exchanged should be valued for consolidation purposes.

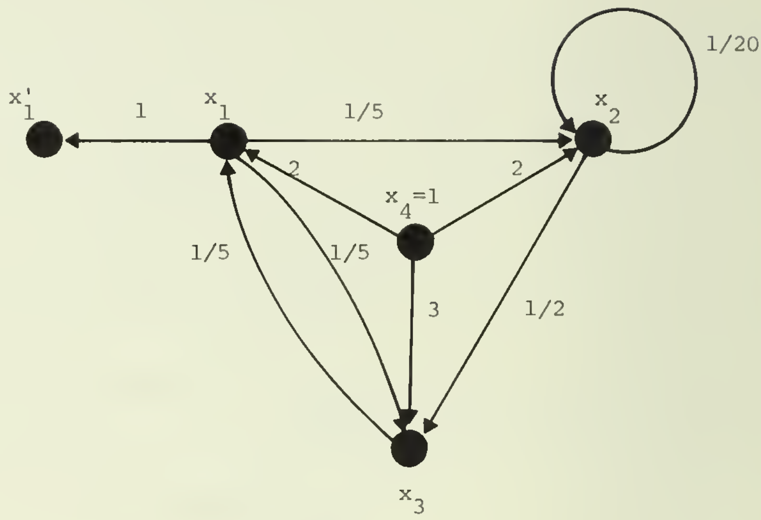
For a three company example Figure 5.18 summarizes the necessary data and supplies a graphical representation.

Figure 5.18a. Data for transfer price problem

Country	fixed & var. costs	quantity produced	expected quantities 1	2	3
1	100	50	0	10	10
2	200	100	0	5	50
3	300	100	20	0	0

The same information may be seen from the graph in Figure 5.18b. Arc transmittances are defined with respect to one unit of intermediate product.

Figure 5.18b. Graph for transfer price problem



In Figure 5.18b node x_4 with a value of one represents the inhomogeneities in the equations for x_1, x_2, and x_3. The latter denote directly the cost per unit of the produced intermediate product. The self-loop at x_2 indicates that five units have to be fed back into the production process if country two produces a hundred units. The arc $\{x_1, x_1'\}$ with transmittance $m_{11}' = 1$ creates a sink. The value of x_1' corresponds to the value of x_1.

From the loops $\{x_1, x_3, x_1\}$ and $\{x_1, x_2, x_3, x_1\}$ one sees that chains between node x_4 and sink x_1' possibly touch more than one loop.

If one wants to express the transfer price of a unit of intermediate product produced in country one, y_{1t}' has to be expressed as a function of the inhomogeneities represented by x_{4t}. Mason's formula (5.14) is applied as follows:

The graph in Figure 5.18b contains three chains between x_4 and x_1'. They are $\{x_4, x_1, x_1'\}$, $\{x_4, x_3, x_1, x_1'\}$ and $\{x_4, x_2, x_3, x_1\}$ and $\{x_1, x_3, x_1\}$. One finds three singulet loops $\{x_2, x_2\}$, $\{x_1, x_2, x_3, x_1\}$ and $\{x_1, x_3, x_1\}$ as well as the non-touching doublet $\{x_2, x_2\}$ and $\{x_1, x_3, x_1\}$ in the graph. It follows that

(5.25) $D = 1 - m_{12} \cdot m_{23} \cdot m_{31} - m_{22} - m_{13} \cdot m_{31} + m_{22} \cdot m_{31} \cdot m_{13}$

(5.26) $$P_1 = m_{41}$$

(5.27) $$P_2 = m_{43} \cdot m_{31}$$

(5.28) $$P_3 = m_{42} \cdot m_{23} \cdot m_{31}$$

(5.29) $$D_1 = 1 - m_{22}$$

(5.30) $$D_2 = 1 - m_{22}$$

(5.31) $$D_3 = 1$$

and

(5.32) $$y_{1t}' = \frac{\{m_{41}(1-m_{22}) + m_{43} \cdot m_{41}(1-m_{22}) + m_{42} \cdot m_{23} \cdot m_{31}\}}{1- m_{22} - m_{13} \cdot m_{31} - m_{12} \cdot m_{31} + m_{22} \cdot m_{31} \cdot m_{13}} . x_{4t}$$

With the numbers in Figure 5.18b one obtains $y_{1t}' = y_{1t} \simeq 3$ as the transfer price of the intermediate product produced in country one. This corresponds to a two node, one arc reduction of Figure 5.18b.

REPRESENTATION AND SOLUTION OF DIFFERENCE EQUATIONS

The specification of an integer valued time shift t_{ij} on all arcs of a graph in addition to the specification of the transmittances m_{ij} uniquely defines linear difference equations describing a system. An example was given in Figure 5.6 for eq. (5.5 - 5.7). Note that eq. (5.8) is an exception.

The question arises if - quite apart from the representation - a graph reduction is possible in analogy to the linear algebraic case.

ANALYTICAL SOLUTIONS

It is well known that in an application of linear integral or summation transforms the solution space of a problem expressed in deterministic linear difference or differential equations is transformed to a (Riemann) space, where the original problem becomes a linear algebraic one again [16,17,18,21,22,39,66]. It is then possible to perform the graph reduction described in the preceeding section. The solution for the transmittances of a reduced GESIFLO-graph have then to be transformed back to the original solution space. This task is either accomplished by using available tables for well known transmittance functions, or - and this is in general not a trivial problem - one evaluates an equation for back-transformation in

cases not so frequently met in practice.

It seems that both approaches are not very pragmatic if one deals with a larger model: in the transformed space one encounters all the difficulties of graph reduction already discussed in connection with linear algebraic systems. So a graph reduction by hand for large and strongly connected graphs is out of the question. In these cases one could only solve the system numerically with standard matrix inversion techniques. But this would more or less automatically imply that back-transformation to the solution space would have to be performed numerically as well [3]. An advantage of this procedure cannot be seen in general.

If one, on the other hand, assumes that an analytical solution in the transformed space has been found and that such voluminous transformation tables as those by Erdélyi, Magnus and Oberhettinger [22] are at hand (which in general will not be the case), still only a small portion of the problems is solved. In practically all relevant cases one has to perform a decomposition of the analytical solution in the transformed space into partial fractions before one can apply the transformation formulas (viz. e. g. [17,18]). For large systems this is already a formidable job.

The value of analytical solutions to larger linear models of economic systems is already questionable under these circumstances. This conclusion is further supported if one considers logical switches, nonlinearities and stochastic terms which might be contained in a model. What remains for practical applications in general is a numerical solution of the systems equations directly in the original solution space.

EXAMPLE FOR NUMERIC SOLUTION

How this approach works can easily be understood from the sales - inventory model shown in Figure 5.6 and eqs. (5.5 - 5.8). The GESIFLO-graph shown does not contain any feedback-loops for which the sum of time shifts over a loop is equal to zero except $\{x_3, x_3\}$ and $\{x_2, x_2\}$ with $t_{33} = 0$ and $t_{22} = 0$. These self-loops can immediately be eliminated by applying eq. (5.13). Therefore cause and effect can be separated for every variable and a logical ordering of the equations is possible. A recursive solution of the system without any matrix inversion can be accomplished. The solution for a period t is achieved by performing the following steps, starting from given initial values and t = 1.

STEP 1: Store All Values Of The State Variables At Time (t-1) And Choose A Value Of The Decision Variable θ_t.

STEP 2: Calculate The Current Values Of The Variables In The Following Sequence:

$$y_{3t} = \frac{1}{1+d} (y_{3(t-1)} + d \cdot y_{3\infty}) \tag{5.33}$$

$$y_{2t} = \frac{a}{a+1} (y_{2(t-1)} + y_{3t}) \tag{5.34}$$

$$y_{1t} = y_1(t-1) + \Theta_t - \frac{b}{a} \cdot y_{2t} \tag{5.35}$$

$$y_{4t} = y_{4(t-1)} + \frac{g \cdot b}{a} \cdot y_{2t} - f \cdot \delta_{\Theta_t > 0} - e \cdot \Theta_t \tag{5.36}$$

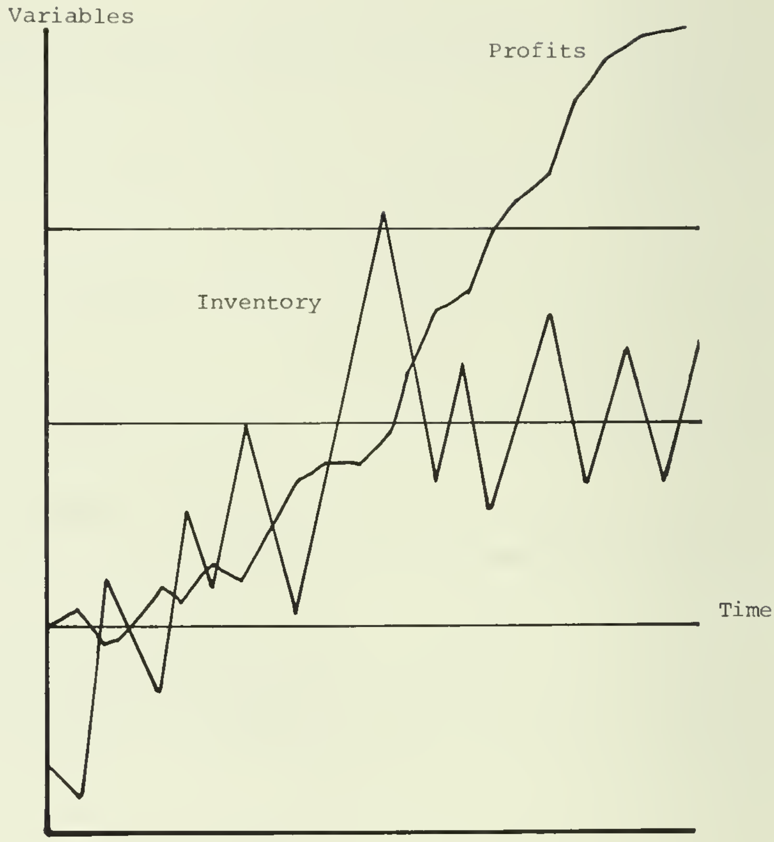
STEP 3: Take t: = t+1 And Go To STEP 1 If The End Of The Solution Interval Is Not Reached. Otherwise Stop.

For a set of parameter values, initial conditions and values of θ_t a typical output for the model variables is shonw in Figure 5.19. The calculation was accomplished with the small IBM CSMP (Continuous System Modeling Program) program which is also shown.

Figure 5.19. Recursive solution of sales-inventory problem

```
INIT
*   PARAMETERS
CONST D=0.05
CONST Y3INF=100
CONST A=0.5
CONST DEC= 50.
CONST B=0.5
CONST G=10.
CONST F=50.
CONST E=3.
*  INIT.VALUES AND DECISIONS
Y1 =15.
Y2 =5.
Y3 =10.
y4 =0.
FUNCTION DLT=(0.,0),(1.,0),(2.,1),(3.,0.),(4.,0.),(5.,1.),(6.,0.),(7.,1.)
         (8.,0.),(9.,0.),(10.,1.),(11.,1.),(12.,1.),(13.,0.),(14.,0.)
         (15.,1.),(16.,0.),(17.,1.),(18.,1.),(19.,0.),(20.,1.)
*  MODEL EQUATIONS
DYNAM
NOSORT
     IF(TIME.LE.O.)  GOTO 1
Y3 =(Y3+D*Y3INF)/(1.+D)
Y2=A*(Y2+Y3)/(1.+A)
DD=AFGEN(DLT,TIME)
Y1=Y1+DEC*DD-B*Y2/A
Y4=Y4+G*B*Y2/A-F*DD-E*DEC*DD
     1 CONTINUE
TIMER DELT=1.,FINTIM=20., PRDEL=1.,
     OUTDEL=1.
PRINT Y1,Y2,Y3,Y4,DD
OUTPUT Y1,Y2,Y3,Y4,DD
PAGE GROUP=3,SYMBOL=(1,2,3,4,*)
```

Figure 5.19. Continued



The model described by eq. (5.33) - (5.36) and the result shown in figure 5.19 represents a typical example for a "What if?" investigation and forward solution. Based on initial values, all endogenous variables may be determined if the user supplies the order decisions Θ_t.

A recursive model solution like it has been described for the above example is not possible, if simultaneities between model variables have to be considered. The underlying GESIFLOG in this case contains loops for which the sum of the time shifts of arcs belonging to the loop is exactly zero. In simple cases one may carry out a loop reduction as it has been done with the above model. For more complicated linear models matrix inversion is employed, for nonlinear simultaneous models searching and approximation methods have to be used. This will be described in chapter 6.

SOME SEQUENCING PROBLEMS

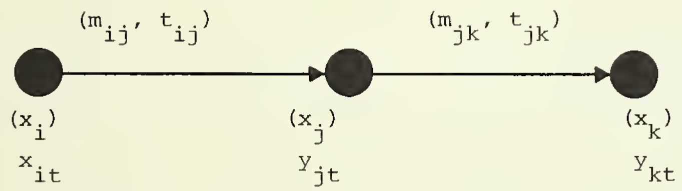
Although graph reduction rules will not be used for the solution of more complicated models, a computer based analysis of the GESIFLOG may aid in the construction, consistency checking, equation sequencing, and the decomposition of a model into simultaneous and recursive segments. Several applications will be described in the sequel. Some algorithms will be supplied in the appendix at the end of this chapter.

LOGICAL ERRORS IN THE MODEL STRUCTURE AND EQUATION SEQUENCING

The structure of a model contains a logical error if time shifts are specified in such a way that an endogenous variable depends on future values of the same or other endogenous variables. Such an error is not likely to occur in one equation. But it may be hidden in cases with larger systems of linear or nonlinear equations. A graph theoretical algorithm may be used to detect such errors.

The following two examples illustrate the problem. Consider Figure 5.20.

Figure 5.20. Cascade arcs

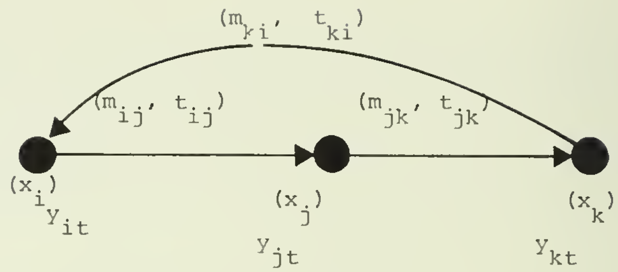


After a reduction of the cascade arcs one obtains directly

$$y_{kt} = m_{ij} \cdot m_{jk} \cdot x_{i(t+t_{ij}+t_{jk})}. \tag{5.37}$$

There is no logical contradiction in the relation, because x_{it} is by definition an exogenous variable or a constant. Using the same reduction in Figure 5.21

Figure 5.21. Feedback loop



one obtains

(5.38) $$y_{jt} = m_{ij} \cdot m_{ki} \cdot m_{jk} \cdot y_j\,(t+t_{ki} + t_{ij} + t_{jk})$$

which, after the underlying cause and effect hypothesis, is a logical contradiction as soon as

(5.39) $$t_{ki} + t_{ij} + t_{jk} > 0.$$

In the appendix to this chapter an (algorithm 3) is supplied which detects such contradictions. The algorithm basically checks for loops of strictly positive length in the graph [64,66]. The algorithm also permits the sequencing of equations for models which have a recursive structure.

SIMULTANEOUS SUB-SYSTEMS

If in a corporate model some of the variables interact simultaneously, it follows from the discussion given above that the GESIFLO-graph of the model contains so called loops of zero length. This means that the sum of the time shifts which are defined on the arcs of the loop is equal to zero Since the number of elementary operations needed to solve a system of n linear simultaneous equations grows proportional to the third power of n, a separate solution of simultaneous subsystems of the model is always preferable to a solution of the entire model.

The appendix to this chapter contains an algorithm (algorithm 4) by which all loops of the GESIFLO-graph of the system are detected and localized. Loops of zero length may thus be identified.

While simultaneous linear subsystems are normally solved by matrix inversion, for nonlinear systems approximation and searching methods have to be used. The speed of convergence of these models strongly depends on

the sequencing of the model equations. The Van der Giessen algorithm [62] (algorithm 5) described in the appendix to this chapter determines a sequence of model equations which is often close to a recursive model structure.

DISTRIBUTED LAG EFFECTS

A chain between any two nodes of the GESIFLO-graph signifies that there is an interaction of the corresponding variables. Very often several chains exist between two nodes. If one calculates the sums of the time shifts of the arcs on these chains then one might notice that they are different. This indicates that the variables are related with different time lags. One observes a so called distributed lag effect: A change in an input variable of the model shows up with different weights and time delays in an output variable.

There are many cases known in theory and practice where a distributed lag effect has to be incorporated into the model structure.

Some practical examples will be given in chapters 6 and 9. In most of the investment models, for example, one assumes that the investment creates a backflow of funds which are distributed in time. In this sense already a simple discounted cash-flow calculation assumes a distributed lag effect. In order to facilitate the study of these effects in a complex model, another algorithm is given in the appendix at the end of this chapter which searches for all chains between any two nodes of a graph. The sum of the timeshifts of the arcs on those chains may also be calculated.

STOCHASTIC VARIABLES

One does not gain any fundamentally new insight into the problem of model representation and analysis, if some of the model equations contain a linear stochastic disturbance term. As such, it is represented like any other exogenous variable or decision variable of a model. If the disturbance terms are cross- or autocorrelated one has the possibility to express this in a GESIFLO-graph. In Figure 5.22 the GESIFLO-graph for a second order autogressive model

$$y_t = \alpha + \beta_1 \cdot y_{(t-1)} + \beta_2 y_{(t-2)} + u_t \tag{5.40}$$

is shown,

FIGURE 5.22. Graph for second order autoregressive model

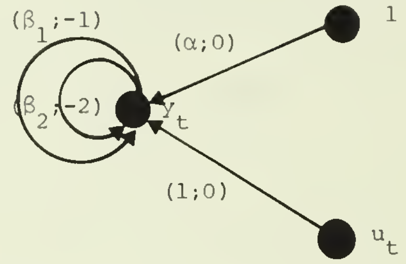
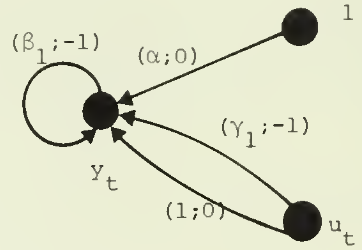


Figure 5.23 represents a first order mixed autoregressive - moving average model [6].

(5.41) $$y_t = \alpha + \beta_1 \cdot x_{(t-1)} + u_t + \gamma_1 \cdot u_{(t-1)}.$$

FIGURE 5.23. Graph for first order mixed autoregressive - moving average model



The solution of such models can in principle be found by methods already described in preceeding chapters. The stochastic inhomogeneities u_t are treated like exogenous variables and may be obtained for instance by one of the numerous random number generators for stochastic simulations [48].

PATH ANALYSIS

Based on some research by Wright [65] several authors have proposed to use signal flow graphs for the identification and estimation of economi models (viz. Goldberger [30], Heise [31]) itself. So far it was always assumed that transmittances m_{ij} in a GESIFLOG were given parameters, e.g. measured or either statistically or subjectively estimated. However, for simple linear models such parameters may be determined by a path or graph analysis only using historical values of the model variables. If the y_{it} denote random model variables then the mean

(5.42)
$$\bar{y}_i = \frac{1}{n} \sum_{t=1}^{n} y_{it}$$

is an empirical estimate of their expected value $\varepsilon\{y_i\}$,

(5.43)
$$\sigma_i^2 = \frac{1}{n-1} \sum_{t=1}^{n} (y_{it} - \bar{y}_i)^2$$

an estimate of their variance var $\{y_i\}$, finally,

(5.44)
$$\text{cov}_{ij} = \frac{1}{n-1} \sum_{t=1} (y_{it} - \bar{y}_i) \quad (y_{jt} - \bar{y}_j)$$

an estimate of their convariance cov $\{y_i, y_j\}$. The GESIFLOG representation and analysis is fully applicable to expected values, since if y_{it} is a random variable defined by

(5.45)
$$y_{jt} = \sum_i m_{ij} x_{it} \quad ,$$

where m_{ij} are transmittances, then

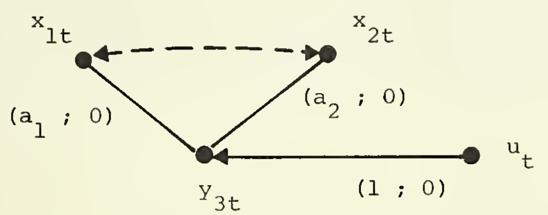
(5.46)
$$\varepsilon\{y_j\} = \sum_i m_{ij} \quad \varepsilon\{x_i\}$$

defines its expected value as a function of, say, the expected values of exogenous input variables x_{it}. However, the variance of y_{it} is defined by

(5.47)
$$\text{var }\{y_i\} = \sum_i m_{ij}^2 \cdot \text{var }\{x_i\} + \sum_{\substack{i \\ i \neq k}} \sum_k m_{ij} \cdot m_{kj} \cdot \text{cov }\{x_i, x_k\}$$

where k has the same extent as i. The variance of y_{it} is a linear function of the variances of the x_{it} only as long as all covariances may be neglected. Additional nodes, arcs and reduction rules are needed in the GESIFLOG if one wants to estimate the transmittances m_{ij} from given observations of the variables using eq. (5.42) to (5.43). Alternatively one may calculate the variances and covariance of dependent model variables using graph reduction rules from given variances and covariances of the source or input variables and given transmittances (viz. e. g. Heise [31, pp. 111-132[). Figure 5.24 supplies an example:

FIGURE 5.24. Path analysis example



It would represent equation

(5.48) $$y_{3t} = a_1 \cdot x_{1t} + a_2 x_{2t} + u_t$$

If cov $\{x_1, u\} \equiv$ cov $\{x_2, u\} = 0$ one obtains

(5.49) $$\text{var } \{y_3\} = a_1^2 \text{ var } \{x_1\} + a_2^1 \text{ var } \{x_2\} + \text{var } u + 2 \text{ cov } \{x_1, x_2\}$$

Assuming that x_{it}, x_{2t} have already been corrected for their means the substitution of x_{2t} in eq. (5.44) using eq. (5.48) would yield

(5.50) $$\text{cov } \{x_1, x_2\} = \frac{1}{a_2} \quad \text{cov } \{x_1, y_t\} - a_1 \text{ var } \{x_1\} .$$

Estimates of the transmittances a_1 and a_2 could thus be determined from given variances and covariances. They would, however, not be least squares estimates, since the variance of u_t is assumed to be known. Using graph reduction rules for larger models would be too complicated and a numerical analysis is preferred if covariances do not cancel.

INFINITE NUMBER OF SOLUTIONS

If the matrix B of the general linear model eq. 2.11 has a rank r (B)<k, where k is the number of endogenous variables in the model, then the systems of equations has an (k - r (B)) infinity of solutions. This can happen either if

- the structure of a corporate model is not completely or not correctly specified, or if
- one is not able to specify equality constraints that restrict the values of the endogenous variables to one value only.

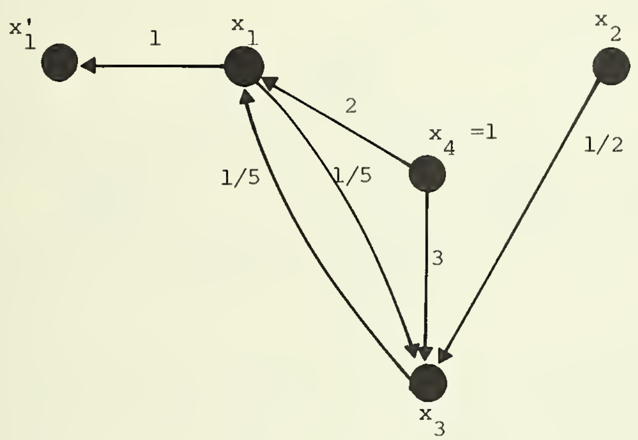
In either case (k - r (B)) endogenous variables may attain arbitrary values. It is then possible to calculate a parametric solution for every variable y_{it} of the system as a function of (k - r (B)) variables y_{jt}, $j \neq i$.

Parametric solutions are often of great interest [10,14,15]. The variables that show up as parameters in a solution may be target values and by adjusting the decision variables of a model it is possible to calculate the values of the endogenous variables of a model which have to be realized to obtain the target values specified.

TRANSFER PRICES

For a demonstration of the target value approach one may again use the transfer price example shown in Figure 5.18a and 5.18b. Assume that one sets the transfer price of one unit of intermediate product delivered by country two to a target value of ten monetary units. One can then ask how high the transfer price of a unit delivered by country one has to be if only country one and country three are consolidated. The graph for the problem is shown in Figure 5.25.

Figure 5.25. Undetermined transfer prices



By application of the reduction rules described previously, one immediately obtains a solution for y_{1t} with y_{2t} as a parameter

(5.51)
$$y_{1t} = \frac{m_{23} \cdot m_{31} \cdot y_{2t} + (m_{41} + m_{43} \cdot m_{31})\ x_{4t}}{1 - m_{13} \cdot m_{31}} .$$

With the given data it follows that the transfer price in country one has to be $y_{1t} = \frac{45}{12}$ [monetary units].

If the parameters of a solution show up as sources in the underlying GESIFLO-graph a parametric solution is easier to obtain than in the general case. For the latter one has to carry out graph reductions that correspond to the Gaussian elimination method [52, p.34]. With bigger problems, it is more advisable to apply the available software for pivoting and rank determination.

EXTENSIONS TO SIGNAL FLOW GRAPH- REPRESENTATIONS

GESIFLO-graphs have been described for the representation of models consisting of linear either algebraic or difference equations. Either simplifications or new graphical elements are needed if inequality, non-conjunctive, stochastic or non-linear relations have to be represented.

The graph reduction rules discussed earlier may not be used for the elimination or solution of such relations. However, the analysis of time shifts and the algorithms supplied in the appendix at the end of this chapter may still be employed as long as the time shifts are not considered as random variables.

LINEAR INEQUALITIES AND PROGRAMMING

Closely connected with problems of underdetermined solutions are those problems in which the values of the endogenous variables are restricted by boundary conditions in the form of linear inequalities.

It has been discussed in chapter 4 that inequalities may be transformed into equations provided that either linear slack variables with non-negativity constraints or quadratic slack variables are introduced. The latter case would correspond to the representation of nonlinear model equations which is discussed later in this chapter. For linear inequalities one would in the first case normally obtain a system of underdetermined equations with an infinite number of feasible solutions. For linear programming problems these solutions are weighted in a performance criterion or objective function. Usually an extremum of this function is looked for.

Both, non-negativity constraints and the type of operator to be applied to the objective function may not be expressed in the GESIFLOGs introduced so far. Consider the example

(6.52)
$$5y_{1t} + 4y_{2t} \leq 10$$
$$y_{1t}, y_{2t} \geq 0$$
$$y_{3t} = 2y_{1t} + 3y_{2t} \Longrightarrow \underline{\text{Max}} \ .$$

Introducing a slack variable y_{4t} one obtains

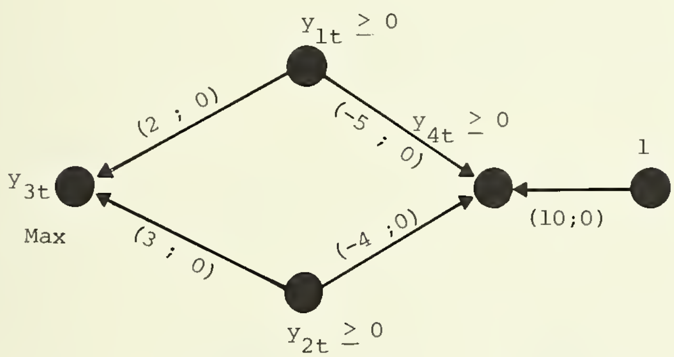
$$y_{4t} = 10 - 5 \cdot y_{1t} - 4y_{2t} \tag{5.53}$$

$$y_{1t}, y_{2t}, y_{4t} \geq 0$$

$$y_{3t} = 2y_{1t} + 3y_{2t} \Longrightarrow \text{Max} .$$

If non-negativity constraints and the maximum operator is directly noted at the nodes of the GESIFLOG, one obtains Figure 5.26 as a representation of the linear program expressed by eq. (5.53).

Figure 5.26. GESIFLOG of linear inequality and programming example



The model and program would correspond to what has been called a "no external decision investigation," since a computer based algorithm would determine all model variables.

LOGICAL SWITCHES AND CONDITIONAL VARIABLES

Frequently one encounters equations in a corporate model that are not elementary [5,47,49]. The form of an equation in these cases depends on the values of certain state- or decision variables or expressions containing the latter. An example was contained in the sales-inventory model discussed earlier in this chapter. The function of accumulated profits, eq. (5.8), was defined differently for cases in which products were ordered, $\Theta_t > 0$ as compared to cases in which no products were ordered, i.e. $\Theta_t = 0$:

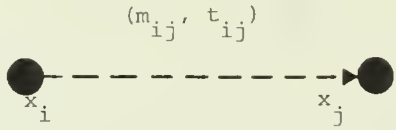
$$(5.54) \qquad y_{4t} = \begin{cases} y_{4(t-1)} + \dfrac{g \cdot b}{a} y_{2t} & \Theta_t = 0 \\ y_{4t(t-1)} + \dfrac{g \cdot b}{a} \cdot y_{2t} - f - e\,\Theta_t & \Theta_t > 0. \end{cases}$$

New types of arcs are introduced in this situation. Arcs which represent terms in an equation which have the same form for all times to be taken into consideration are called conjunctive arcs. Solid lines are used with these arcs.

Non-conjunctive arcs represent terms in an equation whose form and presence depends on logical conditions. These conditions may be defined deterministically or stochastically. In the latter case arcs are only realized with a certain probability.

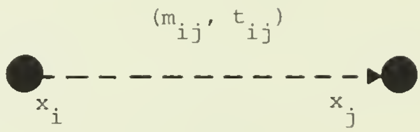
Non-conjunctive, but deterministic arcs are represented by dashes (Figure 5.27).

Figure 5.27. Non-conjunctive but deterministic arc



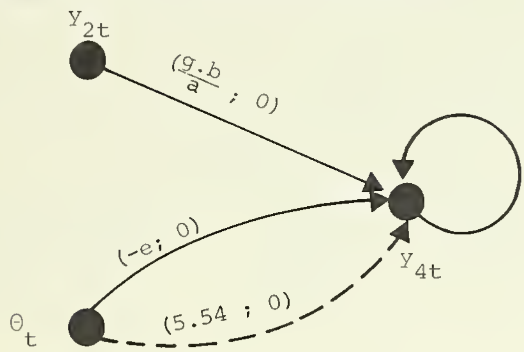
and probabilistic arcs by a mixture of points and dashes (Figure 5.28).

Figure 5.28. Probabilistic arc



For more complicated cases the number of the equation defining an arc is noted as arc transmittance. Figure 5.29 is a representation of eq.(5.54

Figure 5.29. Representation of logical conditions



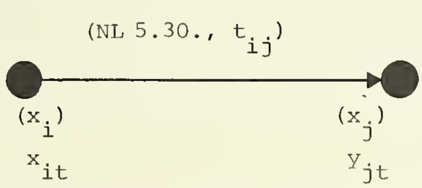
NONLINEAR EQUATIONS

Sometimes there are nonlinear algebraic or difference equations among the equations describing the evolution of a corporate system (viz. [1,5,7, 26,27,35,53]).

In these cases one has to ascertain whether possible difficulties are encountered in the graphical representation, the estimation, or the calculation and simulation of a model.

In a GESIFLO-graph difficulties do not arise from the nonlinearities of the parameters or transmittances of a model, but from nonlinearities in the variables. If such a nonlinear equation is given in explicit form, one can stillindicate cause and effect sequences by directed arcs. Also the specification of time shifts t_{ij} for difference equations is still valid with all its consequences. But the variables do not show up linearily in an equation. It is therefore proposed that one uses a different notation for the transmittances. Figure 5.30 indicates a possible solution.

Figure 5.30. GESIFLO-graph for nonlinear relations



It is indicated that changes of the variable y_{jt} are due to changes in the variable x_{it}. One has to take into account a time shift of t_{ij} time units in the interaction. The latter is nonlinear in the variables (NL) and described in eq. 5. 30.

Similar to the estimation and calculation of a model, a nonlinear representation is only necessary if, first, no functional transformation is at hand that reduces the problem to a linear one, second, a linear Taylor expansion of the relationship is not appropriate. A transformation may be specified at the nodes of a GESIFLOG.

Consider the nonlinear (double-log) marketing model

(5.55)

$$S_t = a_o \cdot P_t^{a_1} \cdot A_{t-1}^{a_2} \cdot D_{t-1}^{a_3} \cdot u_{1t}(\mu_1,\sigma_1)$$

$$A_t = b_o \cdot S_{t-1}^{b_1} \cdot S_{t-2}^{b_2} \cdot A_{t-1}^{b_3} \cdot u_{2t}(\mu_2,\sigma_2)$$

where

a_o, b_o	Proportionality constant
a_i, b_i ; $i = 1,2,3$	Elasticities
P_t	Sales price of a product
A_t	Advertising expenditures for a product
D_t	Distribution expenditures for a product
S_t	Sales of a product
u_{jt} (μ_j,σ_j); $j = 1,2$	Stochastic disturbances with mean μ_j and standard deviation σ_j.

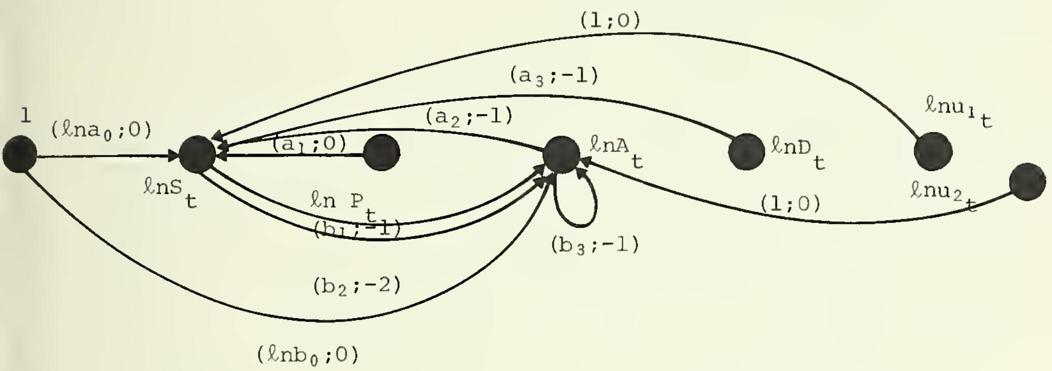
By taking logarithms one obtains

(5.57) $$\ln S_t = \ln a_o + a_1 \cdot \ln P_t + a_2 \cdot \ln A_{t-1} + a_3 \cdot \ln D_{(t-1)} + + \ln u_1$$

(5.58) $$\ln A_t = \ln b_o + b_1 \ln S_{t-1} + b_2 \ln S_{t-2} + b_3 \cdot \ln A_{t-1} + + \ln u_2 .$$

If the logarithmic transformation is indicated at the nodes, one obtains the graph Figure 5.31.

Figure 5.31. Representation of double-log marketing model



A DECISION CALCULUS CASE STUDY

In this section a marketing submodel is employed in order to illustrate variables, equations and the graphical representation of a model. The model describes the effects of detailing on sales of consumer products as it has been described by Little [36] and Montgomery, Silk, and Zaragoza [44]. The implementation of the model at CIBA-GEIGY has been described by Hobday and Reah [32]. Some indications about the use of the modeling procedure will be given as well.

INTENDED USE OF THE MODEL

Based on user supplied market information the model is intended to simulate product sales over a given planning horizon. Subjective estimates of the users describe and quantify the development of the total product market as well as delay, saturation and loyalty effects between detailing and sales. It should be possible to show the response of sales to changes in sales price and detailing policy.

MARKET DESCRIPTION

Discussions with product-management have shown that a finance-marketing submodel should take the following effects between detailing activities and market share of a product into account:

1. The market share y_{1t} of the products is influenced by the retailer's decision to offer the product to consumers or to include it in their assortment. These decisions are influenced by detailing activities and also depend on the firm's decision on the sequence and style products on a detailing leader list are mentioned to the retailers.

2. Detailing does not influence market share directly but by an intermediary variable y_{2t} called "product awareness". This product awareness depends on one side on how well the existence of the product is known, on the other side on the retailer's appreciation on how well it fulfills consumer needs. It is measured or estimated on a market share scale.

3. The products have been introduced into the market already some time ago Product awareness cannot fall below a "loyality level" y_{3t} without detailing. Even with extremely heavy detailing it cannot rise above a "saturation level" y_{4t}. These levels are time dependent and increase or decrease by a percentage r_L / γ or r_s / γ with respect to the levels in the previous period. The constant γ is the number of detailing cycles per planning year, r_L and r_s are growth or contraction rates per planning year.

4. Market share y_{1t} of the products is proportional to product awareness y_{2t}, but it reacts with a delay to changes in the latter (viz. Figure 5.32). If product awareness stays on a constant level then market share converges to the same percentage. Market share y_{1t} in a planning period t is equal to its previous value $y_{1(t-1)}$ plus the difference between product awareness in the same period and market share in the previous period weighted with a smoothing constant α, i.e.: $\alpha\ (y_{2t} - y_{1(t-1)})$. Figure 5.33 is a representation of this relation.

5. Market growth and seasonality effects only change the total market y_{5t} to which the products belong, but not the market share of the products Total market in a period is proportional to the product of its initial value y_{50} a growth factor $(1 + r_m/\gamma)^t$ and an exogenous seasonality factor x_t.

Figure 5.32. Delayed reaction of market share to changes in product awareness

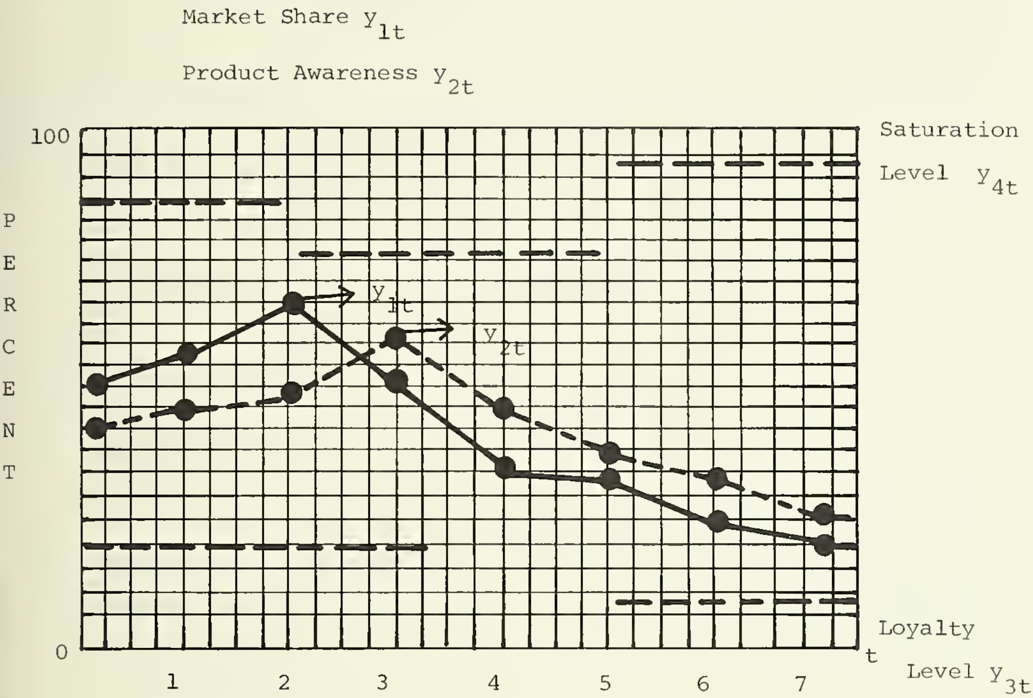
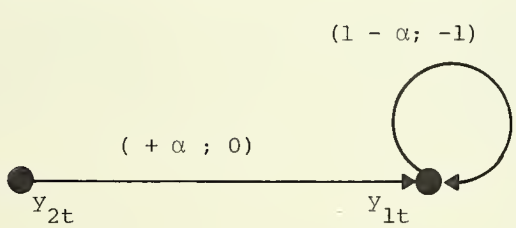


Figure 5.33. Market share equation



6. Product awareness in a period t decreases by a variable y_{6t} if the product is not detailed. This decrease is equal to the difference between the product awarenes in the previous period $y_{2(t-1)}$ and the loyalty level y_{3t}. The difference is weighted by a decay constant d.

7. Product awarenes increases by a variable y_{ijt} above the level that would have been reached without detailing. Variable y_{ijt} is proportional to the difference between saturation level y_{4t} and the product awareness level which one would have obtained without detailing, i.e.

(5.59) $$y_{ijt} \sim (y_{4t} - (y_{2t} - y_{6t}))$$

The proportionality is influenced by decisions on the position j of the product on the leader list and the type i of detailing. A constant e_j describes the relative effectiveness of "solo-detailing" for position j with respect to solo-detailing for position j = 1 of the leader list. The product is discussed alone and without reference to other products with the retailers, if solo-detailing is used.

A second proportionality constant w_i describes the relative effectiveness of type i detailing (e.g. parallel detailing) with respect to solo-detailing. The effects of position j and type i detailing are assumed to be multiplicative. Other effects e.g. due to substitutional or complementary products are thought to be negligible. In a period only one value of i and j may be chosen.

The model is characterized by the following variables, data, and equations:

Exogenous Variables

t	time trend
x_t	seasonality factor of total market

Endogenous Variables

y_{1t}	market share of product
y_{2t}	product awareness
y_{3t}	loyalty level
y_{4t}	saturation level
y_{5t}	total market by quantity

y_{6t}	decrease of product awareness in period (t-1,t)
y_{ijt}	increase of product awareness in period (t-1,t) if type i detailing is chosen for position j of the leader list
y_{7t}	sales by value

Decision Variables

$\theta_{1t} = \theta_1$ sales price of product

θ_{ijt} detailing decision. $\theta_{ijt} = 1$ if type j and position i is chosen, $\theta_{ijt} = 0$ otherwise

Parameters

r_L	change of loyalty level per planning period
r_s	change of saturation level
γ	number of detailing cycles or planning periods per year
r_m	yearly growth rate of total market
$r_p = (1+r_m)^{1/\gamma} - 1$	total market growth rate per planning period
e_j	effectiveness of solo-detailing of position j>1 of the leader list with respect to $e_1 = 1$
w_i	effectiveness of type i > 1 detailing with respect to solo detailing and $w_1 = 1$
α	smoothing constant for market share.
d	decay factor for product awareness

Initial Values

y_{io} i = [1,5] must be specified before a solution of the model becomes possible.

Identities

(5.60) Market Share

$$y_{1t} = y_{1(t-1)} + \alpha\,(y_{2t} - y_{1(t-1)})$$

(5.61) Product Awareness

$$y_{2t} = y_{2(t-1)} - y_{6t} + y_{ijt}$$

(5.62) Loyalty Level

$$y_{3t} = y_{3(t-1)} + r_L/\gamma$$

(5.63) Saturation Level

$$y_{4t} = y_{4(t-1)} + r_s/\gamma$$

(5.64) Total Market

$$y_{5t} = x_t \cdot y_{50} \cdot (1 + r_p)^t$$

(5.65) Decrease in Awareness

$$y_{6t} = d\ (y_{2(t-1)} - y_{3t})$$

Behavioral Equations

(5.66) Sales

$$y_{7t} = y_{1t} \cdot y_{5t} \cdot \Theta_{1t}$$

(5.67) Increase of Awareness

$$y_{ijt} = \Theta_{ijt} \cdot w_i \cdot e_j \cdot (y_{4t} - (y_{2(t-1)} - y_{6t}))$$

Figure 5.34 shows the GESIFLOG for this model. Since it does not possess loops of zero or positive length, equations may be ordered in such a way that a recursive solution becomes possible (viz. appendix to this chapter).

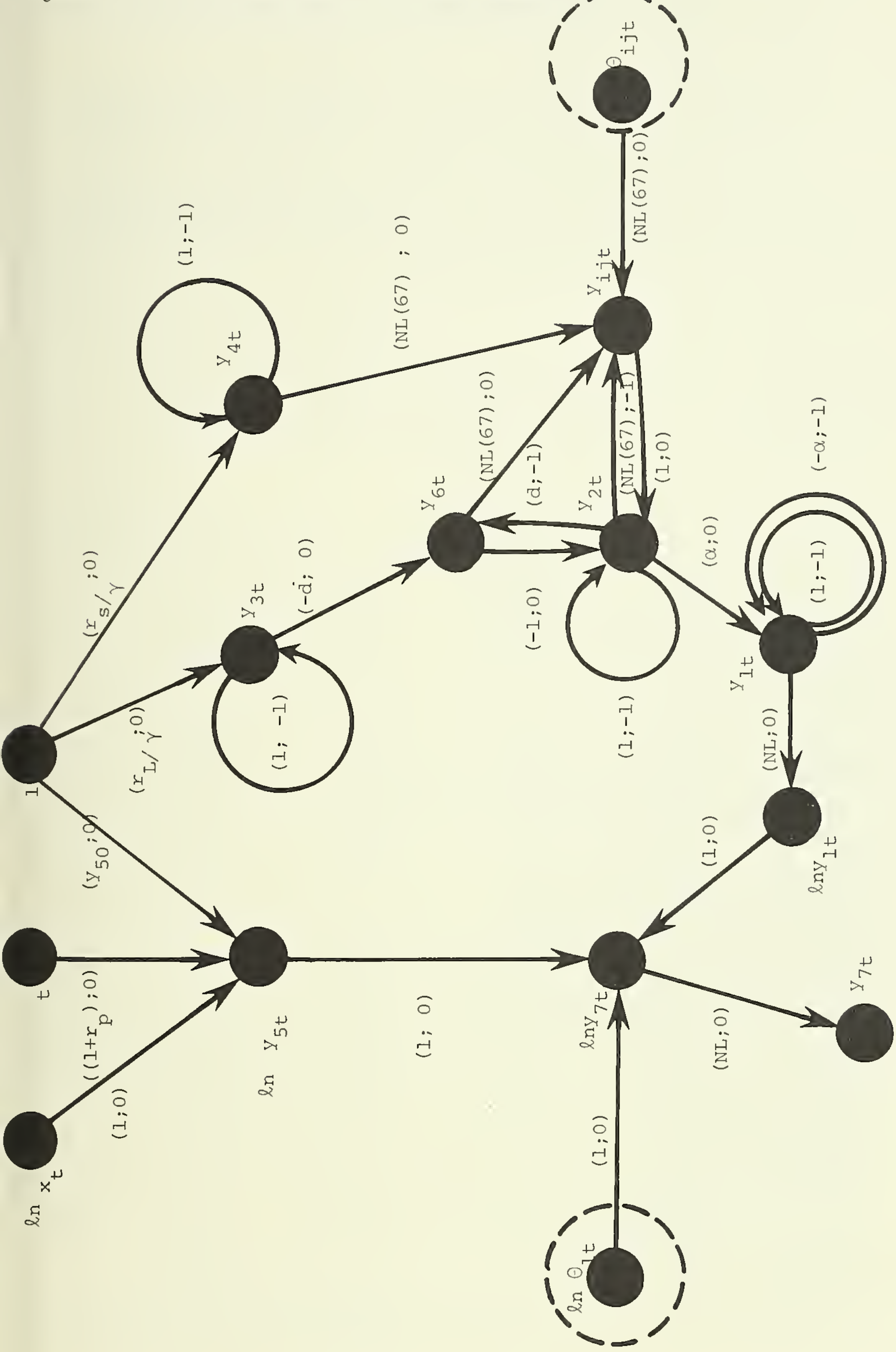
The parameters of the model are subjectively estimated by the users. Figure 5.35 shows an example for a conversational input specification. Note that the smoothing and decay factors α and d are difficult to estimate directly. Questions 10 and 15 are employed for an indirect estimation. The results of a "What if?" investigation are shown in Figure 5.36. A two digit code ij is used to express the detailing decision; 00 corresponds to no detailing, 01 expresses solo-detailing on the first position of the leader list. Smoothing constant and decay factor are printed out as well.

EXTENSIONS

The GESILFOG in Figure 5.34 would contain non-conjunctive arcs if several products are treated simultaneously. Restrictions and logical switches would e.g. follow from the following observations:

- Different products may not be detailed as "solo" on the same position of the leader list in a given period.

Figure 5.34. GESIFLOG decision calculus model



- Certain combinations of detailing plans for different products would either be chosen or deleted if the products are complementary or substitutional.
- The number of detail-men and discussions with retailers would be restricted in a certain planning period.

One would typically obtain a mixed-integer programming problem if the user wanted to determine the detailing decisions which maximize total sales for all products over a given time horizon. In fact such programs were formulated and solved using a heuristics for the case study described (viz. Hobday, Reah [32]).

Figure 5.35. Decision calculus input specification

```
CONVERSATIONAL (1), OR FAST(2) INPUT AND DETAILING CYCLES/YR?
>1 6
Q 01 (MAX. 16 CHARS.) PRODUCT NAME?
>X-PROD
Q 02 (MAX. 16 CHARS.) MARKET NAME?
>Y-MARKET
Q 03 (2) FIRST PLANNING PERIOD?
>1978 3
Q 04 (1) MARKET SIZE - 1000 UNITS PER YR?
>1566
Q 05 (1) MARKET GROWTH RATE ( % PER YEAR)?
>5
Q 06 (1 OR 6) SEASONALITY?
>1.00 1.11 1.25 1.05 0.99 0.89
Q 07 (1) PRICE ($ PER UNIT SOLD)?
>0.9
Q 08 (1) CURRENT MARKET SHARE (%)?
>10.0
Q 09 (4) CURRENT MAX M.S. AND RATE OF CHANCE: MIN M.S. AND RATE OF CHANGE
         (%)?
>12.5 0.5 9.2 0.3
Q 10 (2) MARKET SHARE AFTER 1YR WITH CONTINUOUS NO. 1.SOLO. DET. AND WITH
         NO DETAILING?
>11.5 9.8
Q 11 (3) EFFECTIVENESS OF POSNS  2,3,4 RELATIVE TO POSITION 1?
>0.9 0.75 0.5
```

Figure 5.35. Decision calculus input specification (continued)

```
Q 13 (1) HOW MANY OTHER TYPES OF DETAIL ARE THERE?
>2
Q 14 (2+ UP TO 16 CHARACTERS) TYPE NO., REL. EFF., TYPE NAME?
>1 0.5 TWO PRODUCTS
Q 14 (2+ UP TO 16 CHARACTERS) TYPE NO., REL. EFF., TYPE NAME?
>2 0.7 THREE PRODUCTS
Q 15 (1 OR 7) CURRENT AWARENESS OR AW. 1YR. AGO AND SUBSEQUENT DETAILING?
>10
Q 16 (UP TO 12) DETAILING PLAN?
>00 00 01 02 03 12 23 24 13 11 11
CURRENT SALES VALUE =      26.6
```

Figure 5.36. Results "What if?" analysis

SALES TABLE

	PRODUCT	X-PROD	IN MARKET	Y-MARKET	
PERIOD	DETAIL PLAN	AWARE-NESS	MARKET SHARE	MARKET SIZE	SALES VALUES
1978/2	00	10.00	10.00	295.7	26.6
1978/3	00	9.90	9.98	335.7	30.1
1978/4	00	9.83	9.95	284.3	25.4
1978/5	01	10.96	10.16	270.2	24.7
1978/6	01	11.59	10.46	244.9	23.1
				TOTAL =	130.0
1979/1	02	11.89	10.77	277.4	26.9
1979/2	03	12.01	11.03	310.4	30.8
1979/3	12	11.95	11.23	352.5	35.6
1979/4	23	11.97	11.38	298.5	30.6
1979/5	24	11.89	11.49	283.7	29.3
1979/6	13	11.87	11.57	257.1	26.8
				TOTAL =	180.0
1980/1	11	11.97	11.66	291.3	30.6
1980/2	11	12.05	11.74	326.0	34.4
				TOTAL =	65.0

SMOOTHING FACT. = .212 DECAY FACT. = 0.127

APPENDIX: GRAPH ALGORITHMS

The graphical representation and analysis of GESIFLO-graphs has been discussed in the preceeding sections. Earlier in this chapter we outlined several possibilities on which to base an analysis of a model structure using the time shifts t_{ij} defined on the arcs of a GESIFLOW. In this appendix, weveral algorithms to support such an analysis will be described. The logic of the algorithms is summarized below:

- The algorithm for rank determination (algorithm 1) detects, but does not identify loops in the graph structure. Such loops indicate fee-forward or feed-back relations in the model structure.
- If a graph contains loops of strictly positive length then the model structure contains logical errors which have to be eliminated. Algorithm 2 detects at least one node contained in a loop of strictly positive length in the case there is one. The same algorithm may be used to determine the sequence of model equations to be used in the solution of a recursive model.
- The effort required to solve a model may be reduced if simultaneous submodels or segments in the model structure are detected and independently solved. Algorithm 3 allows the detection and identification of loops of negative, positive, and zero length in the GESIFLOG. Loops of zero length correspond to simultaneous submodels.
- Distributed lag effects between two model variables occur if several chains of different length exists between two nodes of the corresponding GESIFLOW. Algorithm 4 determines such chains and their length
- The sequencing of model equations for a solution of nonlinear models may strongly influence the effort needed for and the convergence properties of a solution. Algorithm 5 is the Van der Giessen algorithm for the sequencing of nonlinear simultaneous model equations.

All algorithms which are described in the following chapters may easily be programmed for a computer. Note that an adjacency or incidence matrix representation of the GESIFLOG would be used for this purpose (viz. [4,34,55,56,50]). If the graph possesses n nodes then e.g. the n x n adjacency matrix $A = (a_{ij})$ could be defined

$a_{ij} = 1$ if an arc $\{x_i, x_j\}$ exists in the graph, or

$a_{ij} = t_{ij}$ if an arc $\{x_i , x_j\}$ exists in the graph and its time shift is t_{ij}

$a_{ij} = 0$ otherwise.

Since no use of arc transmittances m_{ij} is made in the following descriptions, only time shifts t_{ij} will be noted on the arcs of the graphs.

More detailed discussions and proofs for the algorithms used, may be found in the references (viz. Ford [23,24] , Roy [65,66] , Berge [4] , Wille, Gewald and Weber [64], Neumann [50]).

RANK OF NODES (VARIABLES)

The rank r_i of a node x_i in a graph is defined as the maximum of arcs leading from a source x_1 of the directed graph to node x_i. By induction one sees that the maximum rank a node may obtain in a groph without any loops that consists of n nodes is (n-1). In the latter case the chain between x_1 and x_i obviously touches all nodes of the graph.

This may be expressed by

(5.68) $$r_i \leqq n-1 \qquad i = [2,n] \quad . \qquad r_1 = 0$$

If a graph contains loops, the rank of at least one node x_k attains infinite values, because there exists an infinite number of arcs in a chain between x_1 and x_k. Therefore, a necessary and sufficient condition for the existence of a loop is that at least one node in the graph attains a rank

(5.69) $$r_k > n-1 \quad .$$

ALGORITHM FOR RANK DETERMINATION (ROY [54, p. 328], WILLE, GEWALD, WEBER [64, p. 128], NEUMANN [50, p. 53-55])

The ranks of the nodes in a GESIFLO-graph may be determined by the following algorithm:

Algorithm 1

STEP 1: Connect all sources x_i of the graph with a newly introduced node x_o . The graph now has n nodes.

STEP 2: Give all nodes x_i of the graph a label $r_i = 0$. Begin STEP 3 with $x_i = x_0$.

STEP 3: Look for arcs $\{x_i , x_j\}$ that fulfill the strict inequality

$$r_j - r_i < 1$$

and in this case correct r_j to

$$r_j = r_i + 1 .$$

STEP 4: If all ranks of the graph fulfil the inequality

$$r_j \geq r_i + 1$$

for all arcs $\{x_i, x_j\}$ then the ranks are unique and cannot be increased any longer. The graph does not contain any loops in this case. STEP 3 is also terminated if a rank $r_k > n-1$ is attained.

One can show by induction that the algorithm needs a maximum of (n-1) iterations to determine the ranks of the nodes in an acyclic graph. If, therefore, after n iterations one of the nodes has obtained a rank $r_k > n-1$, the graph certainly contains a loop.

The loop may exist, because there is a logical error in the model structure (loop of strictly positive length), or the model contains a cyclical but recursive interaction of model variables (loop of strictly negative length), or some variables of the model interact simultaneously (loop of zero length).

POTENTIAL OF NODES AND THEIR DETERMINATION

The potential λ_j of a node x_j in a directed graph is defined as a real number satisfying the inequality

(5.70) $$\lambda_j - \lambda_i \geq t_{ij} ,$$

where the λ_i denote the potentials of preceeding nodes x_i. Usually potentials are defined with respect to the potentials of the graph. The latter are assumed to have zero potential. Unique and finite potential for all nodes x_i, i=[1,n], of a graph exist only if it does not contain any loops of strictly positive length. Such loops correspond to inconsistencies in the lag structure of the model and have to be eliminated.

The following algorithm may be used. It is an adapted version of Ford's shortest chain algorithm (Ford [24], Roy [54,56, pp. 127-161, 262-292]). The algorithm does not localize a loop of strictly positive length,

but supplies at least one node contained in such a loop.

Algorithm 2

STEP 1: Connect all sources x_i of the graph with a newly introduced node x_0 with time shifts $t_{0i} = 0$. If the graph has no source, connect an arbitrary node with x_0.

STEP 2: Give all nodes x_i of the graph a label $\lambda_i = 0$. Begin STEP 3 with $x_i = x_0$.

STEP 3: Look for arcs $\{x_i, x_j\}$ that fulfill the strict inequality $\lambda_j - \lambda_i < t_{ij}$

and in this case correct λ_j to

$$\lambda_j = \lambda_i + t_{ij} \; .$$

STEP 4: If all nodes x_i, x_j of the graph fulfil the inequality

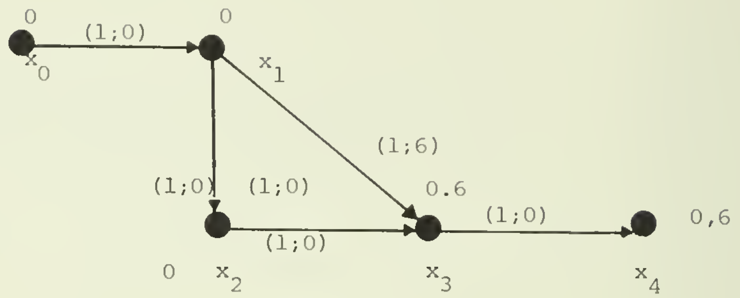
$$\lambda_j \geq \lambda_i + t_{ij} \; ,$$

the labels of the nodes are unique and cannot be increased any longer. In this case there is no time sequencing error in the model.

If a graph with n nodes does not contain any loops of strictly positive length, one can again show by induction that unique potentials λ_i, $i = [1,n]$ may be assigned to the nodes with a maximum of (n-1) iterations one of the algorithm. In case that after (n-1) iterations one of the inequalities (5.70) is not fulfilled, at least one of the nodes x_i, x_j necessarily belong to a cycle of strictly positive length.

Figures 5.37 and 5.38 supply two application examples for the algorithm. The λ_i are indicated at the nodes.

Figure 5.37. Example for labeling algorithm



The graph corresponds to the following equations:

(5.71)
$$y_{1t} = x_{0t}$$
$$y_{2t} = y_{1t}$$
$$y_{3t} = y_{1(t+6)} + y_{2t}$$
$$y_{4t} = y_{3t}$$

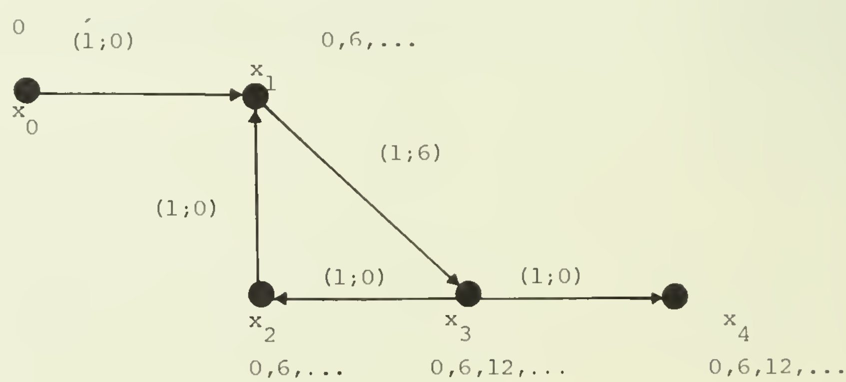
For a correct time sequence the last two equations in a numerical computation are substituted by

(5.72)
$$y_{3(t-6)} = y_{1t} + y_{2(t-6)}$$
$$y_{4(t-6)} = y_{3(t-6)}$$

The model expressed by Figure is recursive. In Figure 5.38 the direction of two arcs has been reversed. The labeling process now does not converge. By substitution the reason is clearly seen. One has for instance the following logical contradiction

(5.73)
$$y_{1t} = x_{ot} + y_{2t} = x_{ot} + y_{1(t+6)}$$

Figure 5.38. Feedback loop with a strictly positive sum of time shifts



Recursive System Of Equations

The algorithm described above may also be used for the determination of the sequence of equations to be used in a recursive model solution. The corresponding GESIFLOG may neither contain loops of positive nor zero lenght in this case. Algorithm 3 described in the next section may be used to identify and localize loops of these two types.

In STEP 3 of the above algorithm it may also be noted for every node which predecessor node has caused the last change in potential. Variables for which the potential of the corresponding node is not changed by STEP 3 may be calculated immediately from the preceeding variables, since all values of the variables for (t-1), (t-2) etc. are known. For the other variables all necessary values of the variable which has caused the last change in potential have to be calculated before the corresponding equation may be solved.

LOOP DETERMINATION

Loops in a graph are important not only because they possibly indicate logical errors in the underlying model structure, but also because one recognizes from a loop of zero length which variables interact with zero time shift. The values of these variables have to be estimated and calculated in a different fashion from the values of variables with lagged interaction. Loops of strictly negative length are interesting, because they indicate feed-forward relations.

An algorithm for the detection and location of loops can be based on the simple observation that nodes which are contained both in a forward chain and a backward chain from a node x_i necessarily have to be on a loop. The following algorithm works on this basis (Willie, Gewald, Weber [64, pp. 139-142]). The steps of the algorithm are:

Algorithm 3

STEP 1: Give a label $\lambda_i = 0$ to all nodes x_i, i=[1,n] of the graph. Let i=1 and λ_1=1.

STEP 2: Check the labels of all nodes x_i. If a follower x_j of x_i has a label λ_j=1 and λ_i has been λ_i=0 then let λ_i=1.

STEP 3: If $i=n$ continue with STEP 4. Otherwise, put $i:=i+1$ and continue with STEP 2.

STEP 4: Put $\lambda_1=2$.

STEP 5: Check the label of nodes x_i. If $\lambda_i=2$ and a follower x_j of x_i has a label $\lambda_j=1$ then put $\lambda_j=2$.

STEP 6: If $i=n$ continue with STEP 7. Otherwise, put $i:=i+1$ and continue with STEP 5.

STEP 7: Eliminate all nodes x_i from the graph that have labels $\lambda_i=2$. If one is not dealing with an isolated node without a self-loop, these nodes belong to a cycle. Eliminate also all arcs from the graph that touch one of these nodes. Renumber the nodes and arcs and go back to STEP 1 (or algorithm 2) if more than one node remains in the graph.

All loops in the graph are localized after several iterations of the algorithm. A disadvantage of the algorithm, e.g. compared to an enumerative algorithm like algorithm 4 (viz. below), stems from the fact that it detects connected loops as a single loop.

If x_1 is only contained in a forward chain, then x_1 is the only node with a label equal to two. In order to speed up the convergence of the algorithm it is therefore advisable to apply it only to those nodes of the graph for which no unique rank has been obtained. A combination of the above algorithm with algorithm 2 makes this possible.

DISTRIBUTED LAG EFFECTS AND CHAIN DETERMINATION

By definition the potential of a node (variable) x_k is equal to the maximum length (lag) between a reference node (variable) and x_k. This is explained by the fact that Ford's algorithm was used as a longest chain algorithm for the determination of the potentials.

If one analyzes a complex corporate model and in particular lagged interactions between variables, not only the longest chain between two nodes of the corresponding graph is of interest, but all the chains that connect two given nodes of the graph. These chains and the sum of their

time shifts may be determined by algorithm 4. Obviously the graph used for this determinationa may not contain any loops of strictly negative length. The maximum number of arcs on a loop between two nodes x_i and x_j could be infinite. As a consequences the sum of the time shifts along such a chain could approach negative infinity. In practice, therefore, all chains between the nodes are searched in a graph that may only contain loops of zero length. The sum of the time shifts of chains that touch loops with a strictly negative length can then be diminished by an integer multiple of the loop sum as long as initial values for the variable x_i exist.

The algorithm is based on a complete enumeration of all chains between the given nodes. The enumeration is accomplished by a decomposition of the original graph into a so called tree (Berge [4, p. 52], Rosenkranz [52, p. 26]).

A tree is a special graph that fulfills the following conditions:

1. There is exactly one node in the graph that has no preceeding node (root of the graph).
2. Every other node in the graph has exactly one preceeding node, but may have several following nodes (branches of the tree).
3. The graph contains at least one sink.

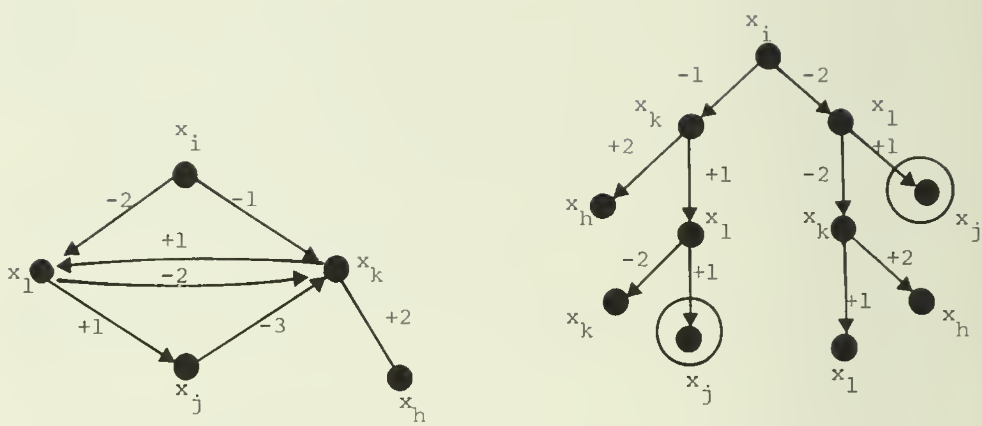
The decomposition of the original graph is accomplished as follows:

Algorithm 4

Node x_i is chosen to be the root of the tree. For x_i and every follower of x_i in the tree one introduces as many followers as there are arcs leaving the node in the original graph. New nodes have the same labels as the corresponding nodes in the original graph. On the new arcs the same time shifts are defined as on the original arcs. For the transmittances this would in general not be true. The construction of a branch of the tree is stopped, first, if node x_j is reached on a branch, second, in the event that the same node is encountered twice in a branch, third, if one of the sinks of the original graphs is encountered.

Figure 5.39 shows an example for the application of the algorithm. The graph of Figure 5.39 contains two chains between x_i and x_j. The sum of the time shifts is +1 and -1, respectively.

Figure 5.39. Tree decomposition



The two loops which are contained in the graph both have a length of -1. The interaction of x_j and x_i will therefore occur with a time shift τ_{ij}, $-\infty < \tau_{ij} \leq +1$, where τ_{ij} is an integer.

In principle algorithm 4 may also be employed to determine ranks, potentials, and loops in a GESIFLOG. However, especially for strongly connected graphs the iterative algorithms described before should converge faster.

EXAMPLES

For demonstration purposes the three algorithms described before have been applied to the analysis of the graph shown in Figure 5.40.

Figure 5.40. Demonstration example

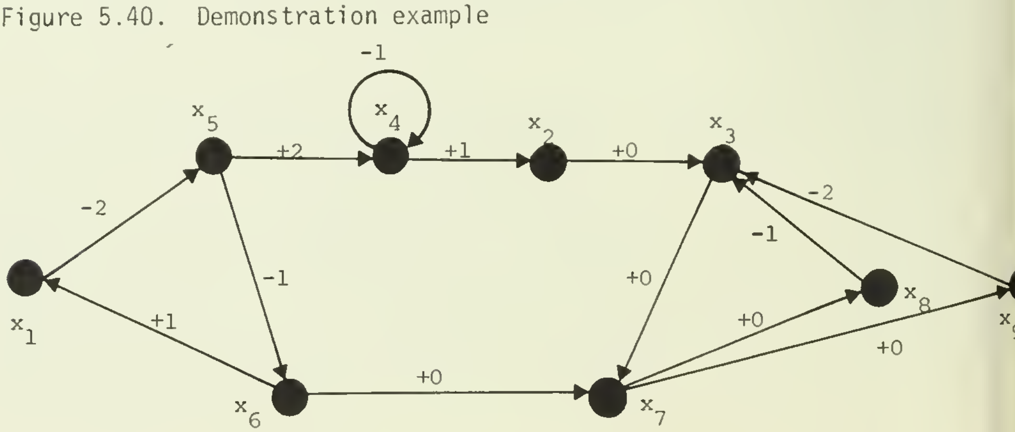


Figure 5.41 exhibits the ranks and potentials of the nodes. The last four columns give the ranks and potentials of the initial and terminal nodes of the graph. Note that the graph does not contain any loops of strictly positive length, but a number of other loops. This can clearly be seen from the ranks of the nodes.

Figure 5.41. Applications of routine RAPOT

RANKS AND POTENTIALS

ARC	INIT	TERM.NODE	TIME SHIFT	RANK1	RANK2	POT1	POT2
1	1	5	-2	27	25	1	0
2	2	3	0	24	29	3	3
3	3	7	0	29	27	3	3
4	4	2	1	26	24	2	3
5	4	4	-1	26	26	2	2
6	5	4	2	25	26	0	2
7	5	6	-1	25	26	0	0
8	6	1	1	26	27	0	1
9	6	7	0	26	27	0	3
10	7	8	0	27	28	3	3
11	7	9	0	27	28	3	3
12	8	3	-1	28	29	3	3
13	9	3	-2	28	29	3	3

By using algorithm 4, two chains between x_1 and x_9 are detected. The first one comprises the nodes $(x_1, x_5, x_4, x_2, x_3, x_7, x_9)$ and has a length of +1, the second chain contains the nodes $(x_1, x_5, x_6, x_7, x_9)$ and has a length of -3.

A first application of algorithm 3 starting with x_1 results in labels of $\lambda = 2$ for nodes x_1, x_5 and x_6; arcs $\{x_1, x_5\}$, $\{x_5, x_6\}$ and $\{x_6, x_1\}$ form a loop of length -2. Before applying again either algorithm 2 or 3, arcs $\{x_1, x_5\}$, $\{x_5, x_4\}$, $\{x_5, x_6\}$, $\{x_6, x_1\}$ and $\{x_6, x_7\}$ may be eliminated from the graph. A further analysis reveals a self-loop $\{x_4, x_4\}$ of length -1 and the touching loops $\{x_3, x_7\}$, $\{x_7, x_9\}$, $\{x_8, x_3\}$ as well as $\{x_3, x_7\}$, $\{x_7, x_9\}$, $\{x_9, x_3\}$. They have a length of -1 and -2, respectively. Since the first chain between x_9 and x_1 touches all the loops, the second chain all loops except the self-loop at x_4, it follows that the value of $x_9(t)$ is

(5.74) $$x_9(t) \sim x_1(t+1),\ x_1(t),\ x_1(t-1),\ x_1(t-2),\ \ldots .$$

SEQUENCING OF NONLINEAR EQUATIONS

Assume that the model consists of a system of n nonlinear equations given in the form

(5.75) $$y_{it} = f(y_{1t}, y_{2t}, \ldots y_{(i-1)t}, y_{(i+1)t}, \ldots y_{nt}) .$$

Note that such a model may be a submodel isolated e.g. by algorithm 4. It is assumed in eq. (5.75) that all values of exogenous, predetermined and decision variables, stochastic disturbances and parameters are already known. Arcs representing these variables and constants are deleted from the GESIFLOG which only incorporates arcs with $t_{ij}=0$ for interacting endogenous variables.

A system of nonlinear equations like eq. (5.75) is either solved by searching or approximation methods. Initial values must be supplied to at least one variable in eq. (5.75), since it is assumed that one cannot solve for the variables explicitely.

Note the following properties if eq. (5.75) is represented by a GESIFLOG:

- A node which has no arcs incident on it corresponds to a variable which does not depend on other variables. Such a variable is either known because an initial value has been supplied to it or because an initial value has been supplied to it or because it recursively depends on other variables which are already known.
- If a variable y_{it} is substituted in eq. (5.75) this corresponds to the introduction of arcs between all predecessor nodes of the corresponding node x_i and all followers of x_i. Only arcs are introduced which have not existed before.
- A self-loop in the GESIFLOG indicates that a variable depends on itself and that it cannot be eliminated by substitution. An initial value must be supplied for such variables. From then on it is assumed to be known.

The van der Giessen algorithm described below tries to sequence the equations in eq. (5.75) in such a manner that they attain a recursive structure after only a few initial values have been supplied [62]. Variable substitutions are used to transform the GESIFLOG. If possible such variables are substituted that depend on the smallest number of other variables.

Algorithm 5

STEP 1: Initialize the equation sequence number k=1. No equation has a sequence number yet.

STEP 2: Determine the number of arcs incident on the nodes x_i of the graph and denote it by λ_i.

STEP 3: If there are $\lambda_i=0$ give a sequence number k to equation i or endogenous variable y_i in the case it has not one already. Put k:=k+1 and eliminate all arcs leaving node x_i.
Else continue with STEP 5.

STEP 4: If all $\lambda_i=0$ then STOP.
Else continue with STEP 2.

STEP 5: Determine $\lambda_j = \min \lambda_i$. Variable y_{jt} is going to be substituted if it has not been used before. Otherwise choose another variable.

STEP 6: Introduce new arcs between all predecessor nodes of x_j to all follower nodes of x_j if they do not exist already. If no change in structure is obtained go to STEP 5.

STEP 7: If a self-loop is obtained for node x_e assign an initial value to variable y_e and eliminate all arcs leaving node x_e.
Continue with STEP 2.

The following example illustrates the algorithm [62, p. 45]. The model is given by

(5.76)
$$\begin{aligned} y_{1t} &= f\,(y_{2t}, y_{3t}, y_{4t}) \\ y_{2t} &= f\,(y_{1t}, y_{4t}) \\ y_{3t} &= f\,(y_{1t}, y_{4t}) \\ y_{4t} &= f\,(y_{1t}, y_{3t}) \end{aligned}$$

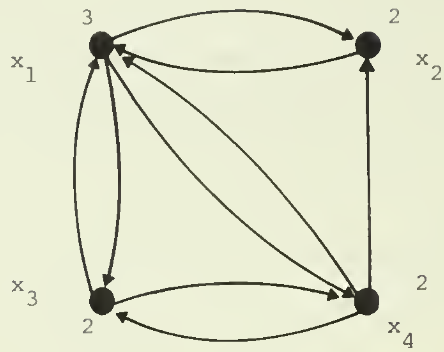
Figure 5.42 is a representation of this structure. The λ_i are indicated at the nodes. The following figures illustrate the steps of the algorithm.

The following result is obtained: initial values y_{1t}^0, y_{4t}^0 are supplied to variables y_{1t}, y_{4t}. With these values eq. (5.76) is recursively solved in the sequence (viz. also Naylor [48, pp. 139-141]).

(5.77)
$$y_{2t} = f\,(y_{1t}^0 , y_{4t}^0)$$

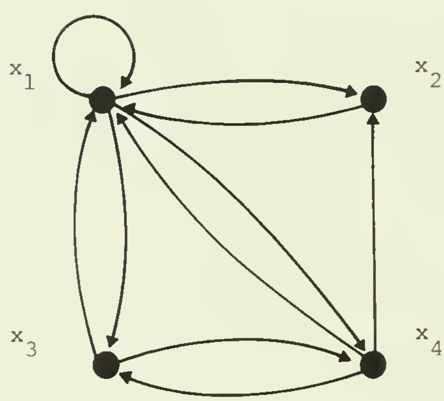
$$y_{3t} = f\,(y_{1t}^0 , y_{4t}^0)$$

Figure 5.42. GESIFLOG of nonlinear model



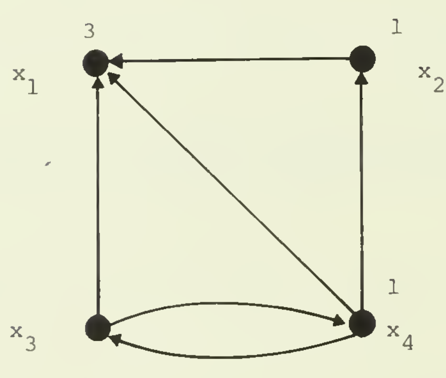
STEP 5: j=2. y_{2t} is going to be substituted. Perform STEP 6.

Figure 5.43.



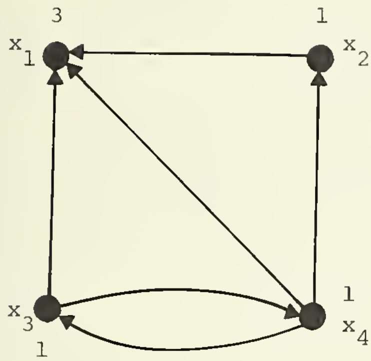
STEP 7: Assign an initial value to y_{1t}

Figure 5.44.



STEP 2: STEP 5. Substitute variable y_{2t}

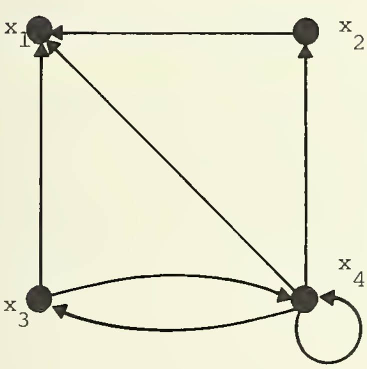
Figure 5.45.



STEP 6: No change in structure.

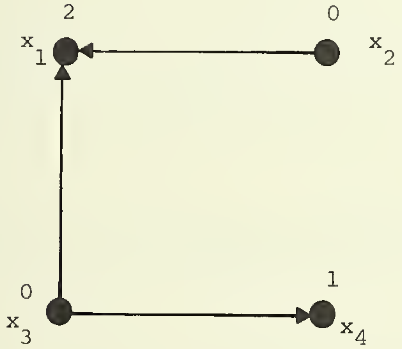
STEP 5: Substitute variable y_{3t}

Figure 5.46.



STEP 7: Assign an initial value to variable y_{4t}

Figure 5.47.



STEP 2, STEP 3: k=1 for equation i=2, k=2 for equation i=3, k=3 for equation i=1, k=4 for equation i=4

$$y_{1t} = f\,(y_{1t}^{0}\ ,\ y_{3t}\ ,\ y_{4t}^{0}\ )$$

$$y_{4t} = f\,(y_{1t}\ ,\ y_{3t}\ ,\ y_{4t}^{0}\ )\quad .$$

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FOOTNOTES TO CHAPTER 5

1. Strictly speaking this in only true for so called Mason Graphs [41, 42]. It is this property that has made that representation more popular than the well known Coates Graphs [11, 12]. Furthermore, the

Mason representation is in agreement with the computer codes in which a value is assigned to the variables left of the equal sign as a function of the right hand side.

2. It should be noted that a system of equations may be represented by several graphs. However, one variable may be defined explicitely only by one single equation!

3. It is important to note that in the representation of Figure 5.15 signal flow is opposed to material flow. For given values x_{1t}, x_{2t} of the output, the requirement for intermediate product y_{3t} would be calculated from the equation $y_{3t} = 2x_{1t} + x_{2t}$.

Estimation, Calculation, and Validation

INTRODUCTION

Within the multi-step model design outlined in chapter 2, it follows from the logic of the modling process that a model is estimated, calculated or simulated only after its inputs have been specified for this purpose. After different estimation, solution and validation methods have been investigated,some of these are chosen as appropriate for a given problem. The actual tests and numerical evaluations of a model are usually carried out after a great proportion of this task has been completed.

A discussion of the estimation, calculation and validation of a corporate model may be centered around computational and practical aspects or, alternatively, around methodological aspects of model building. In this chapter, both aspects will be discussed in parallel. First, the components of a CSPS are described together with their relationships from a computational and practical viewpoint. In the remaining sections, more attention will be given to metholodogical questions.

COMPONENTS OF A CORPORATE SIMULATION AND PLANNING SYSTEM (CSPS)

Over the past ten years, computer manufacturers, consulting companies, and universities have developed CSPSs which may support the corporate model building process.

Most of the corporate models that exist today are tailor-made models. Among tailor-made models one may roughly distinguish between models which are used for "ad hoc" purposes from large models which possibly rely on

deeply structured and large databases and more davanced analytical capabilities. These are most often supported by CSPSs which have been called planning information systems with analytical capabilities.

Differences between models and programming languages or CSPSs used mainly arise from alternative specifications of the intended model use. However, also the available computer and manpower resources determine which model and computer support is chosen. In any case, at the present state of the art such a supporting system will consist of a number of building blocks or components which may be combined in a different fashion for alternative models. This is also the case if e.g. higher level problem oriented programming languages and not special purpose CSPSs and simulation languages are employed.

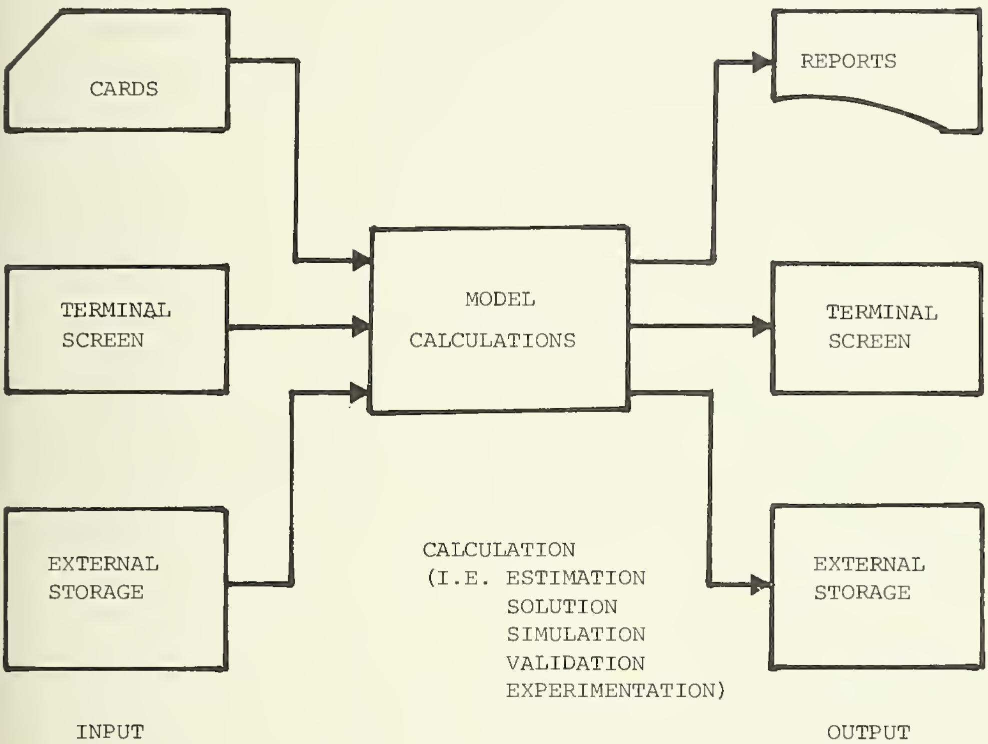
Mainly three building blocks may be distinguished: except for very small ad hoc models corporate model data are not kept in core, but stored in a model database on external storage devices. At least a simple database management system is needed to create, delete, update and maintain this database.

Steps of the model design procedure may be supported by ready made modeling software. Such software consists of macro-instructions, built-in functions, or subroutines which perform frequently encountered modeling tasks.

Although certain standard models may be prepackaged and contained in the modeling software, the model is generally coded in a programming language which may be a general purpose, but also a special purpose simulation and planning language. Apart from being used to code the model structure, the modeling language is used to call on the database, the available software, and to communicate with the model user by input-output instructions (viz. Figures 6.1 and 6.2).

Corporate simulation and planning systems will be discussed more thoroughly in chapter 8. From the discussion of corporate modeling data and equations in previous chapters, one may so far formulate the following requirements.

Figure 6.1. Communication with a corporate model



DATABASE

It seems that quite independently from the system and model used, one has to take two main properties of corporate modeling data into consideration if one intends to construct a CSPS (viz. chapter 3).

On the one hand, relevant numeric data are usually measured discretely in regular time intervals. On the other hand, numeric as well as non-numeric information on model variables are discretely defined with respect to location aspects. As a consequence, corporate modeling data may be organized and structured in "right-angular tables." This very general designation comprises what in mathematical terms is usually understood under a matrix, a column or row vector or a single matrix-element. It is more general, because:

- tables may have more than two dimensions,
- tables may contain non-numeric information, such as variable names or other information on a nominal or ordinal scale,
- table operatons may not necessarily have anything to do with matrix algebra and operations, but may more generally be connected to set operations.

After the discussions in chapters 4 and 5, it goes without saying that the input as well as the output data may be organized in tables. That model calculations may essentially be understood as table operations deserves a short elucidation:

1) The aggregation or disaggregation of model variables may be expressed by set operations (viz. chapter 3). Provided that the elements are organized in tables, these operations are applied to tables.

2) Unrelated to either time series or cross sectional models, the estimation of model parameters using econometric methods is usually accomplished with matrix operations. Estimated or simulated stochastic models are mainly validated or verified by comparing quantities that have been calculated using matrix methods with values of vertain statistical distributions.

3) The stage by stage solution of a corporate model may be understood as a column by column table operation, where the column index corre ponds to the stage index. Row values in a certain column are either calculated in an isolated fashion for recursive models after a correct sequencing of the table rows has been carried out, or alternatively, in groups for sets of interacting variables. The latter is accomplished with matrix inversion techniques for linear models. For nonlinear models eithe an approximation method and again matrix methods become involved or sever iterations in a table column are performed using searching methods. The same observations may be made with respect to model solutions. In the case that techniques of experimental design are used to experiment with a model, in a first step, a model is run repeatedly with different values c the decision variables. The response of the model to such experiments is recorded and for a stochastic model is investigated using such techniques as the analysis of variance or multiple regression techniques. All the operations connected with these evaluations may be represented as table operations.

4) Underdetermined systems of equations or equations containing non-conjunctive terms are solved, as has been indicated above, by either

supplying criteria defining how to rank different model solutions or by specifying exactly the conditions under which logical switches effect qualitative changes of the model structure (viz. chapter 5). So-called pivoting operations as are carried out with linear programming models are closely related to the operations used in matrix inversions and may essentailly be understood as table operations.

LANGUAGE

Equations of a corporate model may in most cases be written as algebraic and difference equations. Considering the discrete definition of model variables with respect to time and location aspects, a corporate modeling language must allow for indexed variables and index calculations. Since model solutions are either carried out recursively or iteratively over a defined time horizon, statements of the langauge are required which allow a repetitive evalutaion of model relations (e.g. DO, END statements). The possibility that the model structure and model evaluations may depend on previous model results or logical conditions calls for statements that control comparison and logical branching operations (e.g. IF, GOTO statements).

It has been mentioned before that corporate modeling data may be both numeric and non-numeric. The modeling language should therefore contain statements which allow the evaluation of both types of information.

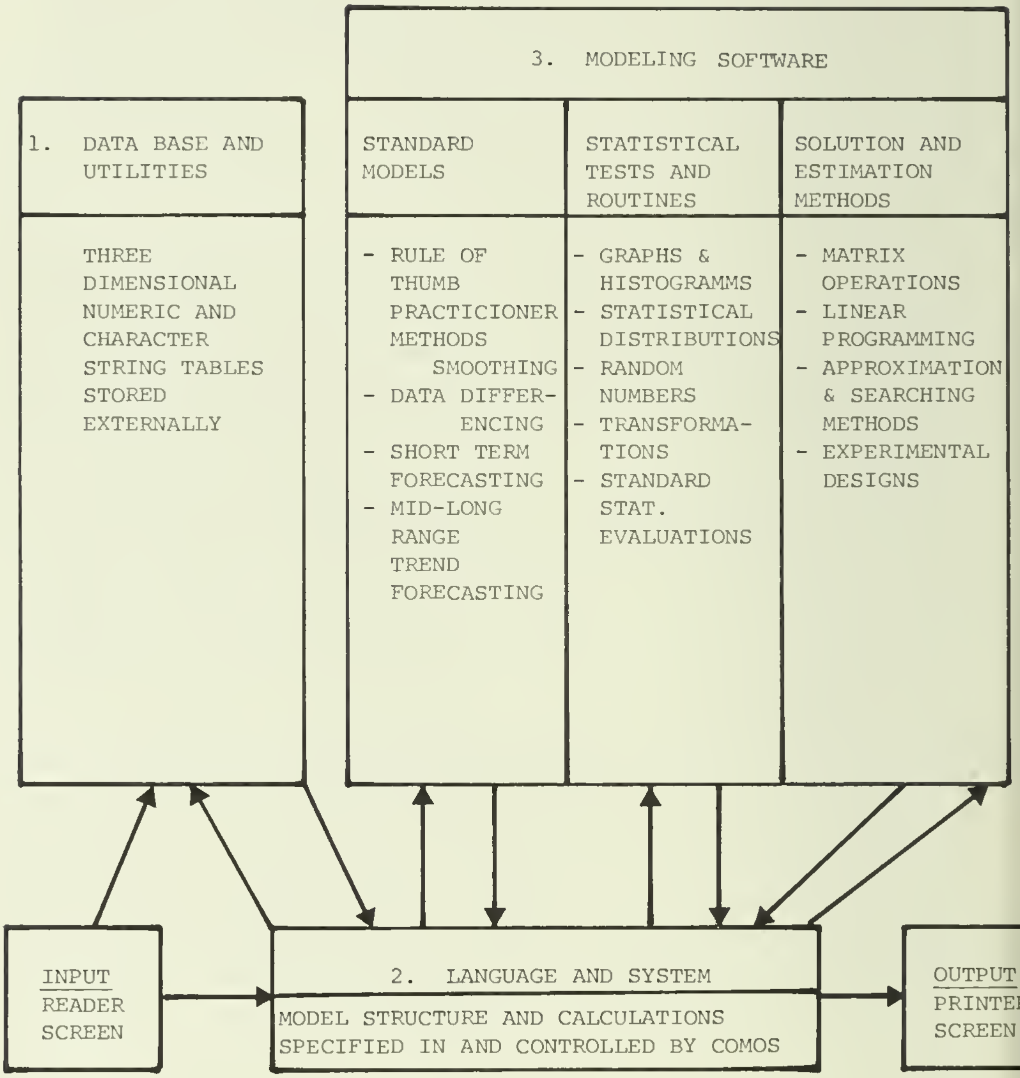
Input-output statements are required to allow for user-model communication and to read from or to write on the model database. Program structure and communiction statements permit the construction of submodels and the invocation of both submodels and modeling software.

SOFTWARE

Frequently encountered modeling tasks in the model design procedure may to some extent be automated by modeling software. Such software may be organized into several blocks as it shown in Figure 6.2 for the CIBA-GEIGY system COMOS.

Corporate modeling software does not substitute special purpose modeling software. One has, therefore, to expect certain sacrifices in its development. In general, these sacrifices will be in the following direction.

Figure 6.2. Components of a corporate planning and simulation system



Regarding computational methods, such a CSPS will not contain very refined and problem oriented methods, but a number of very robust, versatile methods, tests and algorithms. However, it should supply an interface across which more refined methods for special applications may be attached to the systems. Furthermore, since the prerequisites formulated above would still permit a great number of standard methods, care has to be taken that such methods may, if possible, be used in several steps of the model design procedure and may be applied in an extremely modular fashion. The last postulate follows mainly from two observations.

First, a corporate model is often likely to be a large model. In order to facilitate the control and debugging of such a model in general, today a structured and modular program design is chosen. The same principle should be applied to the modeling software.

Second, it is today very likely that a larger industrial firm in a period of about five years either undergoes changes of its internal structure, or its environment or markets change rapidly not only in a qualitative fashion. A corporate model has to be adaptive in the sense that it can track and represent such changes. This together with the observation that a decentralized firm may want to build corporate models for different organizational subunits with the same system also calls for an extremely modular systems design.

STANDARD MODELS AND METHODS IN A CORPORATE SIMULATION AND PLANNING SYSTEM

The following sections will give a description of formal methods and models to be used with corporate models. They may be supported by computer software. However, the description will rather concentrate on applications than on the software itself. A larger number of references indicates more recent methodological developments which may be of interest for more advanced and special applications.

Although the description concentrates on standard formal methods and models, it should be remembered that in many instances informal estimates and guesses of the model users are employed.

In its simplest form, such information and hypotheses are input to a formal model using e.g. input-output statements of a modeling langauge to effect changes in the model database. Informal modeling may be

supported by a CSPS by e.g. supplying a report generator to print and represent tabular data. Modeling software for descriptive statistical data analysis may support both informal and formal modeling. Subroutines to generate plots and histograms, to determine means, standard deviation: maxima and minima of given data series yield valuable information to initiate formal modeling and to represent results in an intelligible forn

SIMPLE GROWTH, PROJECTION AND INTERPOLATION METHODS

Within the planning process of most firms, either linear or exponential growth models are often used to extrapolate from historical values of business variables. Such variables may be endogenous, exogenous or decision variables. Rule of thumb growth projection and interpolation models are not fitted to historical data using statistical techniques, but with a "slide rule" and user judgement. Figures 6.3 to 6.5 illustrate the extrapolation and interpolation of data series by rule of thum models. Their practical importance cannot be underestimated, since these models are flexible enough to incorporate all subjective and a priori knowledge a model user possesses about the development of a data series. For the CIBA-GEIGY middle-range financial planning models, rule of thumb models were frequently employed.

The solution of these models is straightforward and Figures 6.3 and 6 are self-sxplanatory. The same is true for some rule of thumb financial mc dels as they are expressed by an equation containing discounted cash-inflows and outflows, e.g. related to an investment project. From the basic financial model, one frequently calculates such indicators as the return c investment, payback-period net present worth or the internal rate of retu: (viz. van Hoorne [202]). However, for the last indicator, one has already solve an equation for the interanl rate of return i described by

$$(6.1) \qquad \sum_{t=0}^{n} \frac{A_t}{(1+i)^t} = 0$$

where A_t is the net cash flow in period t and n the time horizon of the model. A solution may be carried out by trial and error using present worth tables, or automatically applying an approximation or searching method available in the system.

SMOOTHING AND DIFFERENCING DATA

Simple mechanistic smoothing and differencing models are frequently used to project the development of data series. In contrast to the models that have been described above, such projections are based on the numeric evaluation of several historic (or cross-sectional) data. These evaluations involve the basic four arithmetic operations. Unlike some of the more sophisticated projection methods, these operations are carried out only once, not iteratively, over a data series. In most cases, either linear models like

(6.2) $$y_t = r_t + s_t + u_t$$

or intrinsicly linear models, like

(6.3) $$y_t = r_t \cdot s_t \cdot u_t$$

underly the smoothing and differencing operations. The multiplicative model expressed by eq. (6.3) may be transformed to a linear model by taking logarithms; y_t is the endogenous variable to be described, r_t a trend for which eq. (6.2) could have the form

(6.4) $$r_t = a_0 + a_1 \cdot t + a_2 \cdot t^2 + \ldots + a_m \cdot t_m ,$$

s_t describes a cyclical behavior (i.e. conjuncture, seasonality) of y_t. It could be expressed in trigonometric terms or by

(6.5) $$s_t = b_1 \cdot \delta_{1t} + b_2 \cdot \delta_{2t} + \ldots + b_{p-1} \cdot \delta_{p-1,t}.$$

The coefficients a_j, $j = [0,m]$ and b_i, $i = [1,(p-1)]$ are trend and, for example, seasonality coefficients, respectively. The index p corresponds to the period of the cycle described (i.e. 12 (month) with a seasonality and monthly data), the "dummy variables" δ_{it}, $i = [1, (p-1)]$ have values

(6.6) $$\delta_{it} = \begin{cases} 1 & t = (i + \ell \cdot p) \\ 0 & \text{else} \end{cases} \qquad 0 \leq \ell \geq \frac{n}{p} \text{ , integer}$$

The variable u_t is usually assumed to be generated by a so-called stationary stochastic process, i.e. a process for which the expectation, $\varepsilon\{u_t\}$, is $\varepsilon\{u_t\} = 0$ and its variance and auto-covariances do not depend on time. It is supposed to incorporate all fluctuations of y_t that cannot be attributed to the trend or cycle.

Moving Averages

In the case that $s_t = 0$ and $a_i = 0$, $i > 0$, $t = [1,n]$ and successive values $y_t = a_0 + u_t$ are generated independently, a moving average of past values of y_t is often a good forecast for future values. Its variance is a factor of k smaller than the variance of an individual value of y_t if the average is taken over k values of y_t. Thus, an arithmetic mean of historic values is often used as a forecast. For uneven k, this may be expressed by

$$\bar{y}_t = \frac{1}{k}(y_t + y_{t-1} + \ldots. + t_{t-k+1}),\quad k^* = \frac{k-1}{2} \tag{6.7}$$

Figure 6.3. Exponential extrapolation model with growth rate of the last two historical values

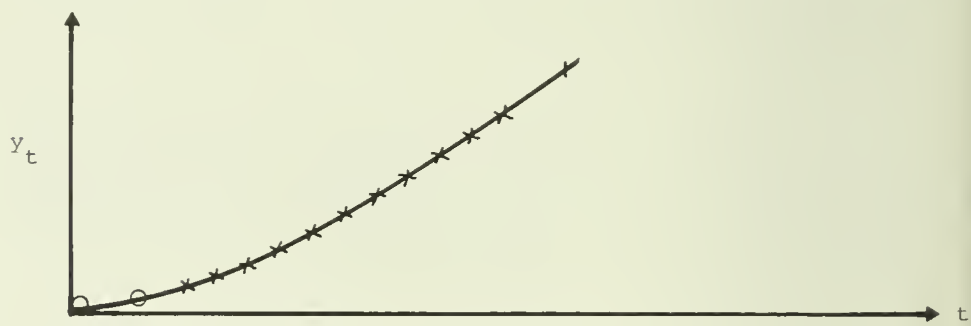


Figure 6.4. Linear interpolation and extrapolation model

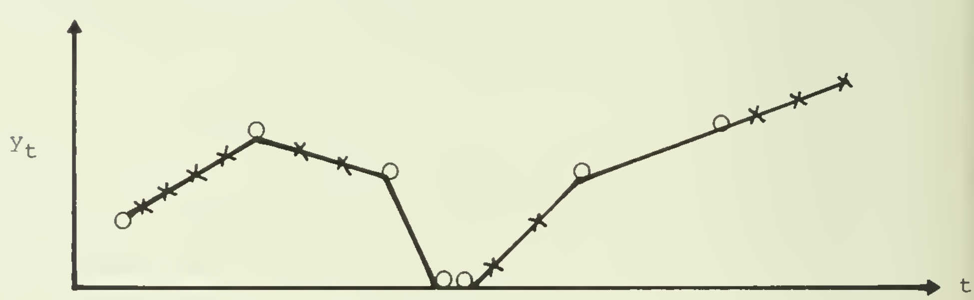
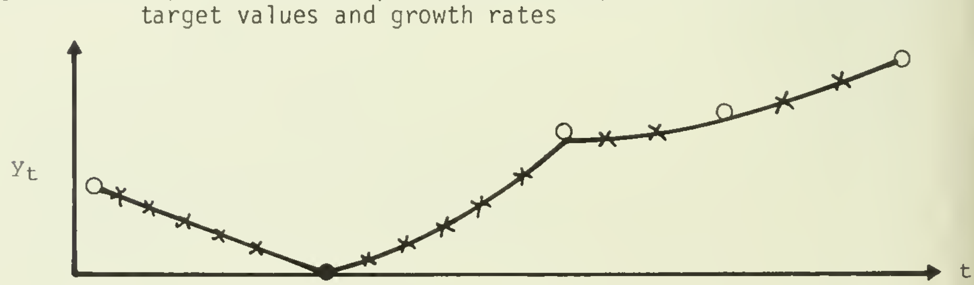


Figure 6.5. Exponential interpolation - extrapolation model with given target values and growth rates



o given historical and target values
x interpolated and extrapolated values

where the average $\bar{y}_t$ could be taken as a τ period ahead forecast for

(6.8) $$y_{t+\tau} \text{ or } \hat{y}_{t+\tau} = \bar{y}_t$$

Clearly the forecast lags behind the actual values by at least half the smoothing period, i.e. $k^* = \frac{k-1}{2}$ for uneven k. This may have great practical disadvantages, especially if the data series is not stationary. The averaging operation expressed by eq. (6.7) may also create cyclical fluctuations in the $\bar{y}_t$ which were not contained in the original series (viz. Theil [199]).

It is important to note that successive moving averages and $\bar{y}_t$ are related by the equation

(6.9) $$y_t = y_{t-1} + \frac{1}{k} (y_t - y_{t-k}) .$$

While this equation facilitates an updating of the forecasts whenever new measurements become available, it should be kept in mind that always the last k values of y_t have to be kept available for this computation. With respect to the computer storage needed, this is a disadvantage compared to some of the methods described below.

Also for non-stationary or stationary but autocorrelated data series there are several simple methods of data inspection and analysis available that allow a crude mechanistic forecasting without any parameter estimation. Such a non-stationarity may be due to the mere presence of a trend or seasonality, as happens for the predominant number of economic time series. An autocorrelation of a data series could also be caused by the omission of other exogenous or endogenous variables from the mechanistic forecasting model. An application of simple smoothing and differencing models is frequently a remedy for such problems.

Differencing

It is well known that a cyclical pattern in y_t will not appear in the smoothed variable $\bar{y}_t$ provided that k is taken to be a natural multiple of the period of the cycle. Seasonal factors may be determined by evaluating the quotients of actual and smoothed time series values. A trend of the form expressed by eq. 6.4 may be eliminated from a series if, instead of using y_t, the data extrapolation is based on values

(6.10) $$\nabla^m y_t = \nabla^{m-1} y_t - \nabla^{m-1} y_{t-1} , \quad m \geq 1 ,$$

where ∇ represents the so-called difference operator with

(6.11) $$\nabla^1 \; y_t = y_t - y_{t-1} \; .$$

Seasonalities or conjuncture cycles in a series may often be eliminated by appropriate seasonal differencing (viz. Box, Jenkins [23]). An operator

(6.12) $$\nabla_p y_t = y_t - y_{t-p} \; , \; p \geq 1,$$

for p = 12 would be used to eliminate seasonals in monthly data.

For the models described, the user has to specify the kind of trend and seasonality he expects to find in a data series. Under the assumption that a data series will obey the same laws in the future as in the past, he may generate extrapolations exhibiting trend, seasonality and conjuncture cycle. This task is very easy to achieve if he uses a CSPS which allows him to quickly graph the results of his calculations and to specify time-shift or lag- and difference operators. Very helpful in practical situations is the more qualitative application of some statistical tests for this basically intuitive model specification. These tests may reveal some properties of the stochastic process which generates a data series or the residuals after a model has been chosen. Well known examples are periodogramms, autocorrelogramms, and partial autocorrelogramms of a series (viz. [23,92,68]).

Some CSPS incorporate software which simultaneously determine seasonality and trend in eq. (6.1) and eq. (6.2). An example is the X-11 Census Method described by Shiskin et al [184] . Cleveland and Tiao [47] have shown that such methods may assume an underlying so-called ARIMA (Autoregressive Integrated Moving Average) model for a time series as is described later in this chapter. Both differencing and smoothing operations are involved. Chan, et al [38] show that differencing operations like eq. (6.10) create another pattern of the unknown u_t in eq. (6.2). than would be obtained by estimating eq. (6.4) by regression. For deterministic trends as expressed by eq. (6.2) the latter method should be preferred, whereas differencing seems to be more appropriate for eliminating stochastic trends.

Criticism

The main advantage of the models that have been described so far is their simplicity from a conceptual and computational point of view. However, their disadvantages may prevent their practical application.

Besides the fact that the models have no explanatory power whatsoever, the assumption that the inertia of a process will guarantee that the future development of a series is determined by unweighted values of the past may be unrealisitc in many circumstances. It has been noted before that a one period ahead forecast using a k period moving average with equal weights actually corresponds to a $(k^* + 1)$ period ahead forecast with all consequences regarding its accuracy. Furthermore, since every value of y_t influences several preceeding and succeeding values of the smoothed series, an "outlier" of y_t may distort the smoothed series for a very long time. Also a structural change in the process generating y_t may easily by disguised. In addition, the trend expressed by eq. (6.4) and the corresponding differences defined by eqns. (6.10 - 6.11) assume unit autocorrelation between successive actual or differenced values of y_t instead of autocorrelation coefficients absolutely between zero and one. Very often it may prove to be very unrealistic to assume that the process possesses such a strong memory. These deficiencies have lead to the development of more refined methods which will be briefly described in the following section.

WEIGHTED MOVING AVERAGE MODELS

The disadvantage of the intuitive forecasting methods may sometimes be avoided by applying models that use weighted moving averages to generate the smoothed series. A variety of weighted moving average models is known so far, but the models first proposed by Holt, et al [114, pp. 258-298] , Winters [215] , and Brown [32] seem to have found industrial application most frequently. Brown selected models in which the historical time series values in a moving average were multiplied with geometrically decreasing weights, i.e. instead of eq. (6.7) he took

$$(6.13) \qquad \bar{y}_t = \alpha . y_t + (1-\alpha) y_{t-1} + \ldots + \alpha(1-\alpha)^n \cdot y_{t-n}$$

with the smoothing constant α, $0 < \alpha \leq 1$ and $\lim_{n\to\infty} \sum_{i=0}^{n} \alpha(1-\alpha)^n = 1.$

Equation (6.8) now takes the corresponding form

$$(6.14) \qquad \bar{y}_t = \alpha . y_t + (1-\alpha) \cdot \bar{y}_{t-1} \, .$$

A comparison reveals that a smoothed value and forecast $\bar{y}_t$ may be calculated from its previous value and the most recent value of y_t, once on initial value $\bar{y}_0$ and the smoothing constant α are given. Historical values of y_t are not necessary to update the forecasts. If one defines

$$(6.15) \qquad e_t = y_t - \bar{y}_{t-1}$$

as forecasts error, where $\bar{y}_{t-1}$ is used as an estimate of y_t, one obtains

$$(6.16) \qquad \bar{y}_t = \bar{y}_{t-1} + \alpha .\ e_t \ .$$

Hence, the old value of the smoothed series is corrected by the product of the forecast error and smoothing constant to give the new value of the smoothed series. On the contrary, the corresponding correction in eq. (6.9) still depends on the first historical value y_{t-k} within the smoothing period. In practice, one has found that values $0,05 < \alpha < 0,2$ are often a good compromise between a good adaption to real changes in the data and a possible overreaction to merely stochastic disturbances in the generation of the y_t. A consequence of the indicated values of α is that the smoothed series $\bar{y}_t$ is not influenced for a very long time by its initial value $\bar{y}_0$. One may see this from a back-substitution of $\bar{y}_{t-1}, \bar{y}_{t-2} \ldots \bar{y}_0$ in eq. (6.14).

Brown, Meyer [33] and D'Esopo [60[have shown that a correspondence between the time dependent coefficients of a forecasting trend polynomial of the form

$$(6.17) \qquad r_{t+\tau} = a_0\ (t)\ .\tau + \ldots . a_m\ (t)\ .\ \tau^m$$

and the exponentially weighted moving averages

$$(6.18) \qquad \bar{y}(1) = \alpha .y_t + (1+\alpha)\ .\ \bar{y}_{t-1}^{(1)}$$

$$\bar{y}_t^{(k)} = \alpha .\bar{y}_t^{(k-1)} + (1+\alpha)\ .\ y_{t-1}^{(k-1)} \quad , k = [2,(m-1)]$$

may be established and that the polynomial minimizes the discounted square error sum S_t,

$$(6.19) \qquad S_t = \sum_{i=0}^{\infty} (1-\alpha)^i\ .\ (y_{t-i} - a_0\ (t) - a_1\ (t).(-i) - \ldots -$$

$$\ldots -a_m(t).(-i)^m)^2$$

For a first order model, as is described by the smoothing equation (6.14), $\bar{y}_t$ is an estimate for $a_0(t)$. More generally, the trend polynomial eq. (6.17) is fitted locally at time t, the fitting parameters, $a_i(t)$, $i=[1,m]$ may be calculated analytically using the $\bar{y}_t^{(k)}$, $k = [0, (m-1)]$

and the trend polynomial is used to generate forecasts $y_{t+\tau}$ for time $(t+\tau)$. The fitting parameters are updated or adapted, whenever new measurements become available. So far, mostly trend polynomials up to $m=2$ (triple exponential smoothing) were used in practice. Transformations or trend and seasonal differencing of the series to be forecasted, allow the application of the same smoothing techniques to a wider class of trend functions (viz. Box, Cox [21]). A number of authors have described smoothing models that take seasonals and cycles into consideration. The books by Lewandowski [138] and Granger and Newbold [92] seem to give the most recent and exhaustive discussion of such models and their application.

The smoothing methods described above have found widespread industrial application, especially in the area of short term demand forecasting for inventory control. In most cases, models either due to Brown [32] or Winters [215] are contained in the software that is nowadays offered by most computer manufacturers.

Criticism

Smoothing techniques have been criticized by a number of authors, notably by Box and Jenkins, because they do not employ a systematic model design procedure including the steps of model specification and identification, estimation and validation. Usually the smoothing model and the weight distribution is assumed more or less arbitrarily. This certainly saves a lot of computer time and is a pragmatic approach, whenever a large number of relatively short time series (i.e. $n < 20$) has to be forecasted and influence factors cannot be identified. However, for more careful, but descriptive investigations of the behavior of key variables in a model, statistical identification tests or tests of parameter significance and goodness of fit should be used. A misspecified forecasting model, e.g. resulting from the choice of a particular moving average model when an autoregressive model should have been used, will in general result in forecasts which do not have such a property as a minimum mean square forecast error.

SOME METHODS OF STATISTICAL ANALYSIS AND FORECASTING

Models that use statistical analysis for short- to mid-term descriptive forecasting have especially been described by Box and Jenkins [23] and Granger and Newbold[92] long-term descriptive trend forecasting notably by Lewandowski [138] , Späth [191] , Gregg, Hossell and Richardson [95] Levenbach [137]. For an application oriented overview, see [37]. Explicative models containing several endogenous, exogenous and decision variables are the predominant research-subject of the econometricians (viz. textbooks Malinvaud [144], Theil [196-199] , Wold [216, 157] , Dhrymes [65] , Maddala [142]).

The application of such models does not only require a combination of the programming language used within a CSPS with available standard models, but calls for a "battery" of statistical tests and estimation and solution methods in the CSPS. Some of these models, tests and methods will be indicated below.

BOX-JENKINS ANALYSIS AND FORECASTING

Box and Jenkins [23] (viz. also Nelson [164] , Granger and Newbold [92]) do not only consider moving average models, but more generally so-called autoregressive integrated moving average models (ARIMA) as may be expressed by

(6.20) $$\emptyset (B) \; \nabla^d y_t = \Theta(B) \cdot u_t \quad ,$$

where B is the lag operator defined by $B^p y_t = y_{t-p}$,∇ the difference operator. The functions $\emptyset(B)$ and $\Theta(B)$ correspond to polynomials in the lag operator. The roots of the polynomial equations $\emptyset(B) = 0$; $\Theta(B) = 0$ must lie outside the unit circle. A model expressed by eq. (6.20) is said to be ARIMA (p, d, q) if it may be expressed by

(6.21) $$(1-\emptyset_1 \cdot B^1 - \emptyset_2 \cdot B^2 - .. - \emptyset_p B^p) \cdot \nabla^d y_t = (1-\Theta_1 \cdot B^1 - .. - \Theta_q \cdot B^q) \; u_t \; ,$$

where the $\emptyset_i$, i = [1,p] , Θ_j , j = [1,q] are so-called autoregressive or moving average parameters, respectively.

The Box-Jenkins models most often investigated are probably first and second order integrated moving average models, ARIMA (0,1,1), (0,2,2) or mixed models of the type ARIMA (1,d,1).

Frequently not the original y_t series, but a transformed series is used in the estimation. Examples for such transformation are the logarithmic or inverse transformation [21] ; frequently, the y_t series is also already deseasonalized. Sometimes the models also contain a constant intercept term. An example for such applications will be given below.

As the difference operator used with the above models indicates, models often describe basically nonstationary stochastic processes. Differencing the endogenous variable y_t is necessary to be able to estimate a model of the stationary differenced series.

Proper substitutions of the lag and difference operators leads to the following explicit expressions

(6.22) $$y_t = y_{t-1} + u_t - \Theta_1 \cdot u_{t-1}$$

for the ARIMA (0,1,1) and

(6.23) $$y_t = 2y_{t-1} - y_{t-2} + u_t - \Theta_1 \cdot u_{t-1} - \Theta_2 \cdot u_{t-2}$$

The first (non-stationary) model may be shown to also describe a exponential smoothing model, whereas the ARIMA (0,2,2) model is used to take non-stationarities due to a stochastic trend into consideration (Box-Jenkins [23, pp. 103-111, pp. 166-170]).

Box-Jenkins models are identified by calculating and testing the autocorrelation function or periodogramm and the partial autocorrelation function of the variable y_t if its historic values indicate a stationary behavior. For non-stationary series appropriate differencing should be carried out before one determines the number p of autoregressive parameters and q, the number of moving average parameters to be included in a model. Although a lot of intuition (viz. Chatfield [43]) still has to be applied in the specification of a Box-Jenkins model, the model design steps are roughly used as follows (for a short description, see Newbold [165]):

1. The model specification and identification is carried out by applying lag and difference operators to the original series y_t, $t = [1,n]$ and inspecting its periodogramm or autocorrelation function and its partial autocorrelation function. If a stationary process generates successive values of y_t, the estimated autocorrelation function $r(k)$ defined by

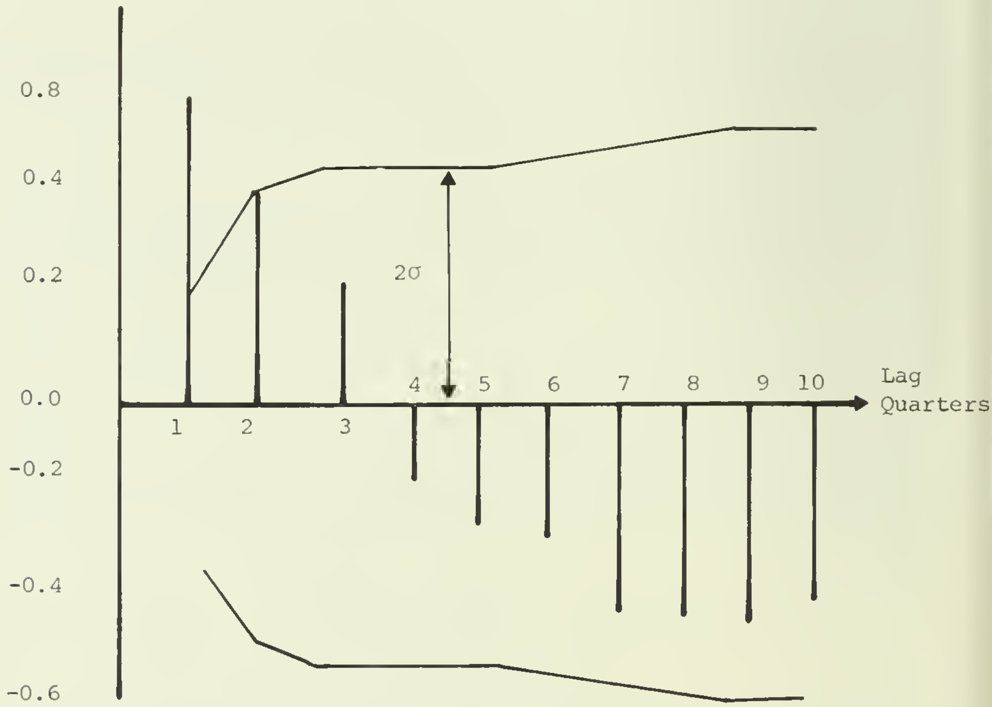
$$(6.24) \qquad r(k) = \frac{\sum_{t=1}^{n-k} (y_t - \bar{y})(y_{t+k} - \bar{y})}{\sum_{t=1}^{n} (y_t - \bar{y})^2}$$

may be expected to decrease and fade out or be cut off with increasing values of the lag k, $\bar{y}$ is the arithmetic mean of the y_t. The corresponding periodogramm of the West German textile production index (viz. Figure 2.5) shown in Figure 2.6 would not exhibit this behavior; its autocorrelation function would show maxima at $k = 4m$, $m = 1,2,..$. This indicates the presence of a seasonality. Figure 6.6 shows the autocorrelation function and its $2\,\zeta$ confidence intervals for the series y_t^*, where

$$(6.25) \qquad Y_t^* = \nabla_4\, y_t \quad \text{and}$$

∇_4 is the seasonal operator for quarterly data.

Figure 6.6. Autocorrelation function of differenced textile production index, West Germany (Figure 2.5)

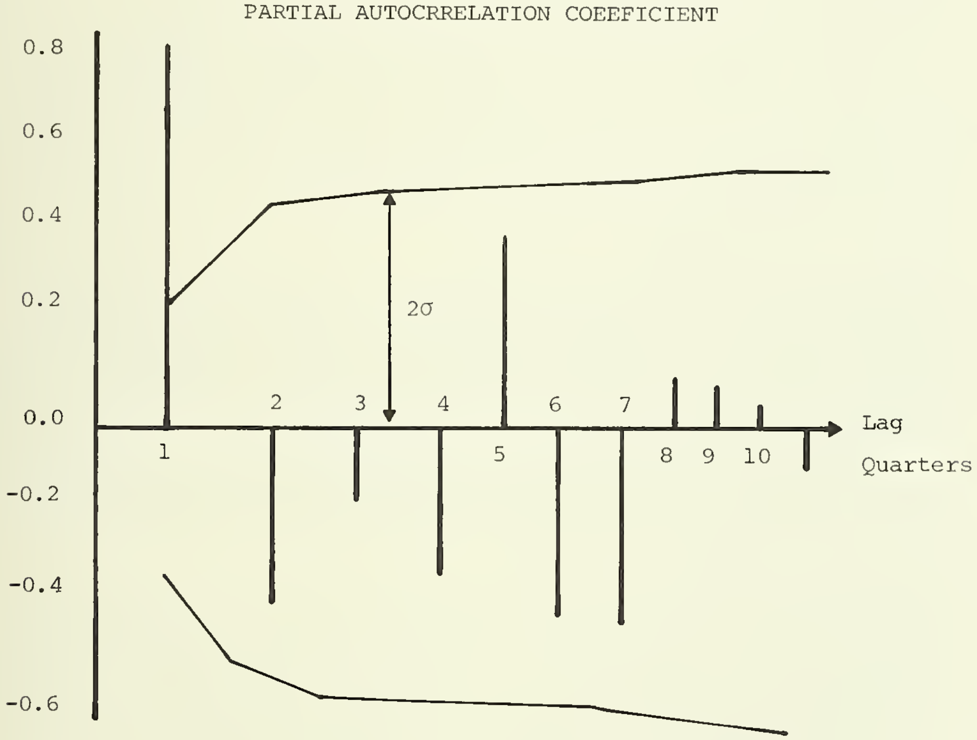


The estimated partial autocorrelation function of the differenced series together with its 2 σ confidence limits is shown in Figure 6.7. It may be defined as the coefficient $\emptyset_{kk}$ obtained from successive solutions of the linear system of equations

$$r(j) = \emptyset_{k1}\, r(j-1) + \emptyset_{k2} \cdot r(j-2) + \ldots + \emptyset_{kk}\, r(j-k) \tag{6.26}$$

where j = [1,k] and the r(j) are the values of the autocorrelation function defined by eq. (6.24) (viz. Box-Jenkins, [23, p. 64-66, pp. 82-84]).

Figure 6.7. Partial autocorrelation function of differenced textile production index, West Germany (Figure 2.5)



In the case that the autocorrelation function of a stationary series is sharply cut off for a $k = p$, one would try to incorporate the properties of a moving average process of order p in the model, if $r(k)$ only decreases slowly one would look for a cut-off of its partial autocorrelation function perhaps at $k = q$. In that instance, one would try to fit an autoregressive model of order q. It is also possible to obtain some information about a mixed (p,d,q) ARIMA model from such an inspection [23, pp. 173-187]).

Figures 6.6 and 6.7 indicate that one might among others try to fit an ARIMA model (1,0,1) defined by

(6.27) $$(1-\emptyset_1 \cdot B^1)\, y_t^* = (1-\Theta_1 \cdot B^1)\, u_t$$

to the data series shown in Figure 2.5.

2. After a model has thus been specified and identified, its parameters $\emptyset_i$, Θ_j and the variance σ^2_{ut} of the residuals are estimated applying the least squares or maximum likelihood principle. In the first case, one minimizes

(6.28) $$LS = \sum_{t=1}^{n} u_t^2$$

using either linear or, more generally, non-linear multiple regression techniques (viz. e.g. Marquardt [145, 135, 192]). By using such techniques, estimates of the model parameters and their variance-covariance matrix are obtained at the same time. This information may now be used to

3. Test and verify hypotheses about the significance of parameters using Student's t-test or the F-test provided that, apart from stationarity, also the independence and normality of the residuals u_t may be assumed. The meaning of model verification and validation is to a large extent determined by the intended use of a model. With Box-Jenkins models the estimated models are supposed to produce minimum mean square error forecasts $\hat{y}_{n+\tau}$, $\tau \geq 1$, of the endogenous variable. Since a great number of correctly specified and estimated models may deliver such forecasts, after the principle of parsimony usually the model requiring the smallest number of parameters is chosen. Such a model might be found by "overfitting" techniques, i.e. alternative and more complicated models are identified and estimated. Such models are exposed to tests of goodness of fit, randomness of the residuals of the fitted model (viz. Durbin [68, 69] , Box and Pierce [24] , Box, Jenkins [23 pp.287-299], Granger, Newbold [91, 92] and descriptive measures of predictive accuracy such as

Theil's information inaccuracy test or U-test [197, 198,196, pp. 31-48], Wold's Janus test [85, pp. 229-235], the Von Neumann ratio [91] or Williams and Kloot's regression test [211, 119]. With such tests of predictive accuracy, one usually does not use all measurements of the endogenous variable for the identification and estimation and compares the remaining measurements ex-post with the forecasts supplied by the model.

If one estimates the model expressed by eq. (6.27) for the West German textile indix data (viz. Figure 2.5) using all except the last five measurements and calculates Theil's U-statistics according to[197,12]

$$(6.29) \qquad U = \left(\frac{\sum_{t=n+1}^{n+\tau} (y_t - \hat{y}_t)^2}{\sum_{t=n+1}^{n+\tau} y_t^2} \right)^{1/2}, \quad 0 \leq U \leq 1$$

one obtains U = 0.032 which indicates a good predictive accuracy. In Figure 6.8 the results together with the values of the parameters are given.

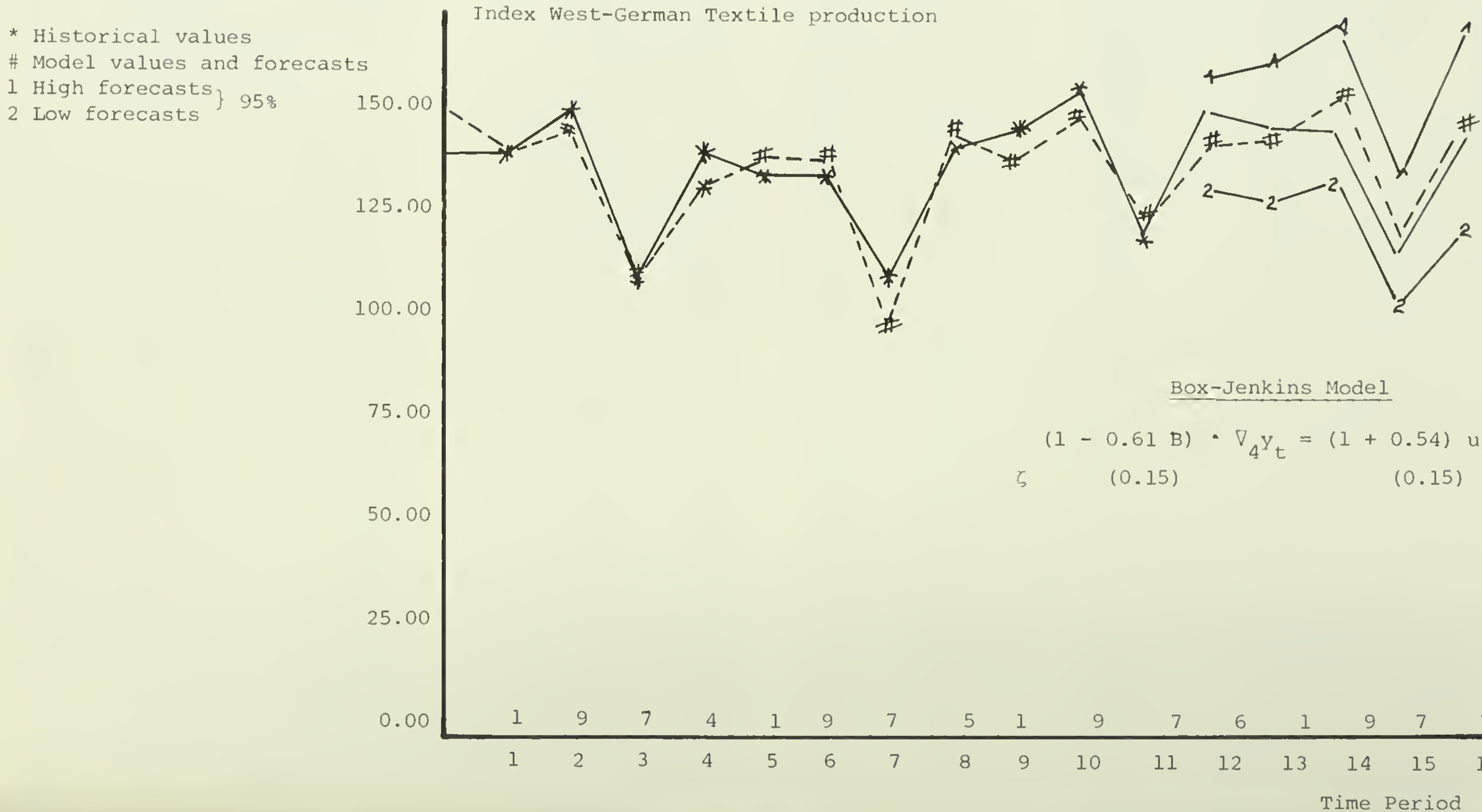
Technically, Box-Jenkins models and methods are relatively easy to implement in a CSPS. The test "battery" and estimation and matrix methods should be available in an extermely modular fashion, because they may be applied with only minor modifications to the specification, estimation and validation of trend and explicative econometric models as well. Difficulties with the technique mainly arise from its use.

Criticism

Box-Jenkins models are determined from a statistical specification and identification procedure. Unlike the models previously discussed, a model is not assumed a priori, but follows from a data analysis in which one "lets the data speak for itself" (viz. Newbold [165], Chatfield [43]). It is, therefore, not suprising to find a large number of investigations in which Box-Jenkins models outperformed other types of models (e.g. [162,92,105,86]). However, several authors have noted disadvantages connected with Box-Jenkins analysis and modeling.

In general, Box-Jenkins models and forecasts are not easy to establish as the automatic forecasting models mentioned before. It requires

Figure 6.8. Results of Box-Jenkins model applied to West-German Textile production index data.



more statistical expertise and time to specify, run and evaluate a model. The use of Box-Jenkins models in this situation is not feasible if e.g. within a corporate modeling project a larger number of product time series has to be forecasted. The future will show whether it is possible to develop robust Box-Jenkins software which automates the model building and forecasting process. Since at present, the model specification is left to the user he also has the choice to specify bad models. Another practical disadvantage is the fact that univariate Box-Jenkins models require a large number ($n > 30$) of measurements for the specification and estimation process.

A number of authors have noted that Box-Jenkins models as described basically by eq. (6.20) possess a specific functional form. The models are linear in the parameters and the variables and the structure do not change over time. It should therefore be possible to find many examples in which other models outperform Box-Jenkins models. Reports on such models are in an increasing number available (viz. e.g. Chatfield, Prothero [42,43], Granger, Newbold [92], Geurts, Ibrahim [86], Makridakis, Wheelwright [143]).

TREND ANALYSIS AND FORECASTING

Similarly to the more short-term oriented forecasting models which have been discussed above, with trend models an endogenous variable is normally described as a function of time only. However, in contrast to exponential smoothing, not only the functional form but also the parameters of the trend models are assumed to stay constant over time. They are not fitted locally,but over the whole time span that is thought to be representative for the development of a variable. Updating the parameters of a trend model in general necessitates its complete reestimation. In this sense, trend models are not adaptive and are mostly used to express mid- to long-term laws underlying the generation of values of a variable. Trend models are usually estimated using linear and nonlinear multiple regression techniques. It should be noted, however, that the application of weighted least squares techniques (viz. Draper, Smith [67, pp. 77-81]), Matt, Griese [96,147]) provides the link between the trend and the short-term forecasting models described. From a computational viewpoint, it is in most cases also possible to generalize a mere trend model to an

explicative model by incorporating other variables than time into it.

Quite apart from such extensions, the functional form of a trend curve often implies an economic hypothesis about the development of a variable and care should be taken that it is compatible with any a priori knowledge the model user possesses.

This might not be so clear if only polynomials of the form

$$(6.30) \qquad y_t = \sum_{v=0}^{m} a_v t^v \quad t = [1,n], \quad m \leq 3$$

are fitted to the data and used for their extrapolation. Such polynomials could be understood as a Taylor expansion of more complicated models that are nonlinear in the parameters a_v. However, already a deterministic exponential trend model of the form

$$(6.31) \qquad Y_t = e^{a+b \cdot t}$$

where a is a constant and b a growth rate, incorporates an economic hypothesis: For small time increments Δt one can write

$$(6.32) \qquad y_t - y_{t-\Delta t} \approx \Delta t \cdot b \cdot y_{t-\Delta t}$$

and one sees that an increase or decrease of the variable is induced by its previous values. The exponential saturation model

$$(6.33) \qquad y_t = y_\infty (1 - e^{a-bt})$$

implies that increases of y_t $(b>0)$

$$(6.34) \qquad y_t - y_{t-\Delta t} \approx \Delta t \cdot b \ (y_\infty - y_{t-\Delta t})$$

are proportional to the product of the difference between saturation level y_∞ and previous value $y_{t-\Delta t}$ and a rate constant b.

Frequently, a logistic hypothesis has been used in trend forecasting to relate increases of the variable y_t to the product of the previous level $y_{t-\Delta t}$ and difference between the maximum level y_∞ and the previous level:

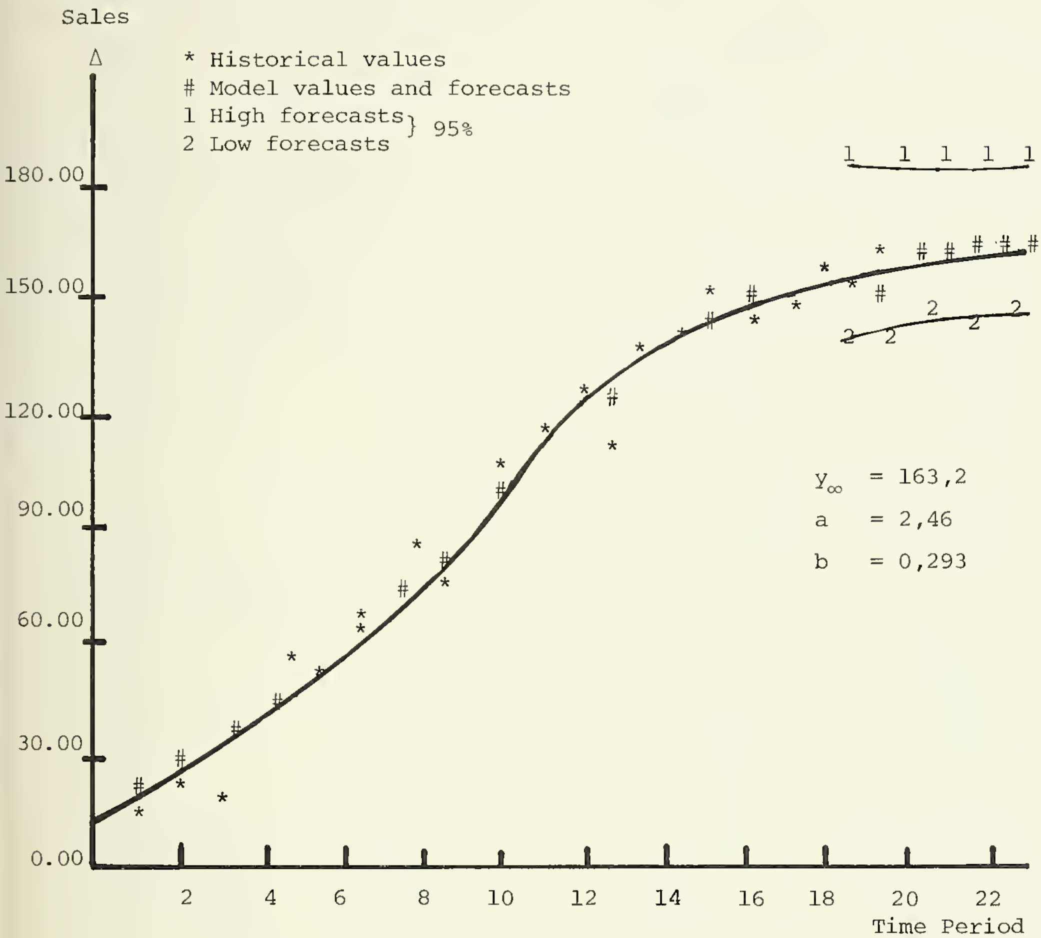
$$(6.35) \qquad y_t - y_{t-\Delta t} \approx \Delta t \cdot b \cdot y_{t-\Delta t} \ (y_\infty - y_{t-\Delta t}) \ .$$

This, for small Δt, essentially continuous hypothesis leads to the well-known trend model

$$(6.36) \qquad y_t = \frac{y_\infty}{1 + e^{a-bt}} \qquad a>0 \ , \ b>0 \quad ,$$

where a is an integration constant defining the initial value of y_t. Figure 6.9 shows an estimation example for such a model.

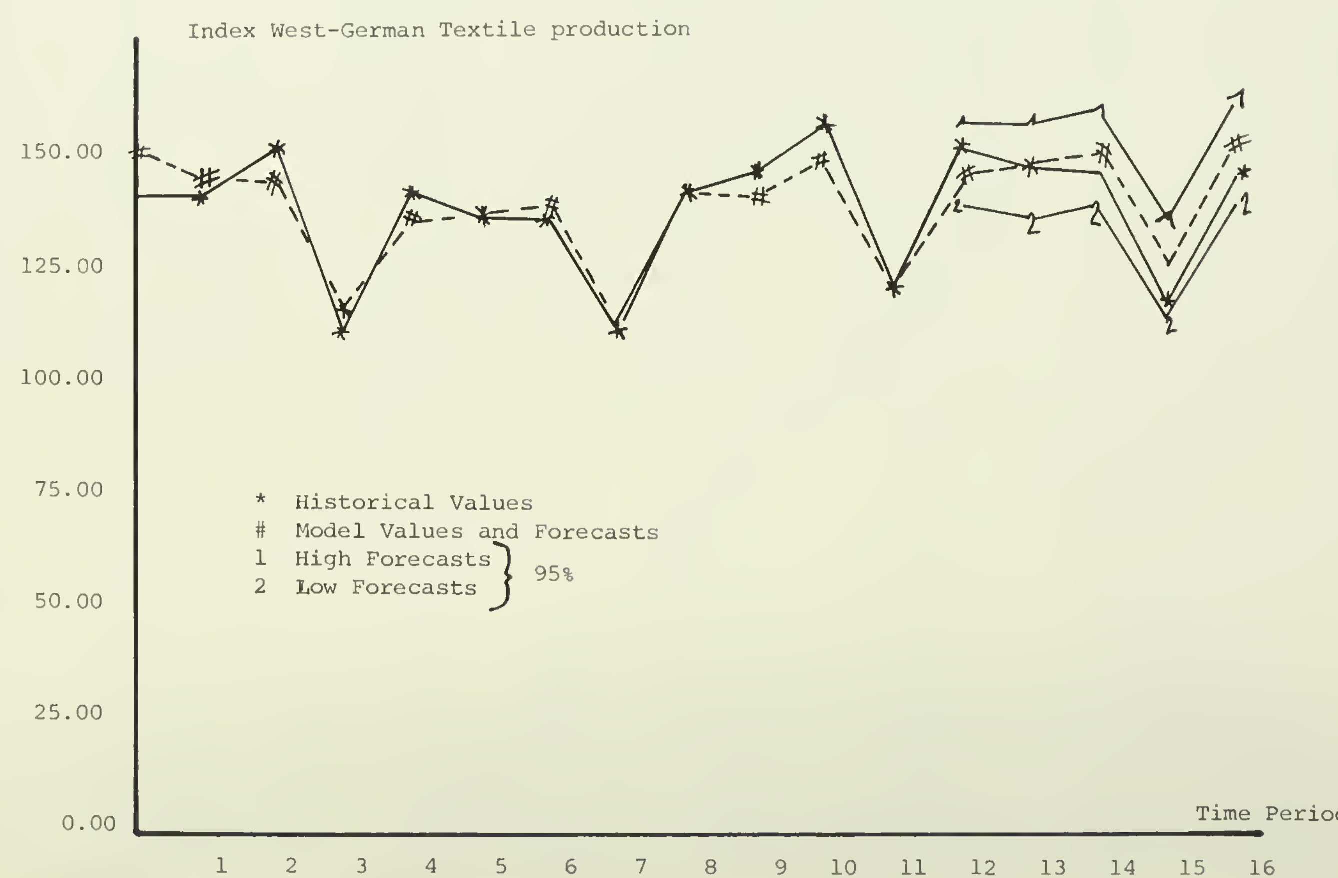
Figure 6.9. Logistic trend model



The logistic trend model and its generalizations are perhaps the most frequently used models if one wants to describe the introductory and saturation phase of long living consumer and investment goods over a mid- to long-range time horizon [95,138,193]. It incorporates the properties of an exponential growth model in the introductory phase and the properties of an exponential saturation model for large values of t.

In the case that the rate constant b of the underlying diffusion process is assumed to be influenced by other exogenous variables, $\underline{X}_t$ or decision variables $\underline{\Theta}_t$, one could use the explicative and generalized logistic model

Figure 6.10. Results of seasonal logistic model applied to West-German Textil production index data.



$$(6.37) \qquad y_t = \frac{y_\infty}{1 + e^{a-t(b_0 + \sum_i b_i x_{it} + \sum_j c_j \Theta_{jt})}} ,$$

where the b_i and c_j are additional parameters of the model.

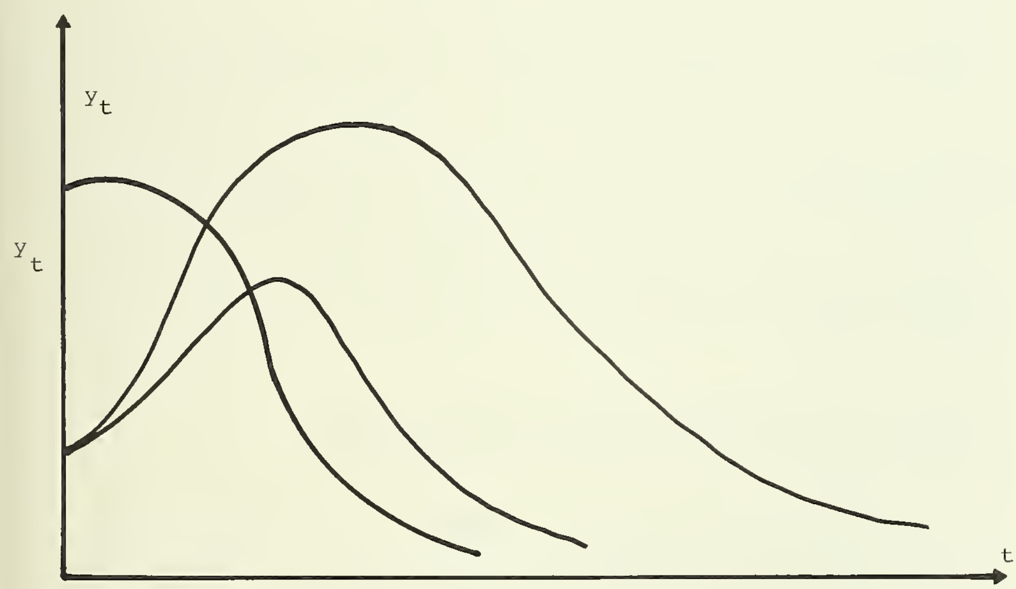
Figure 6.10 supplies an example for such an application. A seasonal logistic model was estimated to forecast the West German textile production index. Unemployment rate and private consumption were used as explanatory variables. Theil's inequality coefficient is U = 0.039, however, the historical fit is better than for Figure 6.8.

Also very useful for life-cycle forecasts is the endogenous competition model

$$(6.38) \qquad y_t = (\tau+t)^m \cdot e^{a-bt} \quad ; \tau>0,\ m>0,\ b>0$$

shown in Figure 6.11 (viz. Brockhoff [30], Lewandowski [138], Spä̈th [191].

Figure 6.11. Competition trend model



As with the other trend models briefly described, one may, at least for natural values of m, formulate hypotheses that result in the trend curve shown: assume for example that the variable y_{1t} describes sales of a product that substitutes sales of competitor products described by a variable y_{2t}. If increases $\Delta_{(1)} y_{1t}$ of y_{1t} are thought to be proportional to the sales of the competitors one has

(6.39) $\Delta_{(1)}y_{1t} \sim b \cdot y_{2t} \cdot \Delta t$.

If an addition decreases $\Delta_{(2)}y_{1t}$ of y_{1t} are assumed to be proportional to the level of y_{1t} already attained via

(6.40) $\Delta_{(2)}y_{1t} \sim -b \cdot y_{1t} \cdot \Delta t$,

it follows that changes of y_{1t}, Δ_{y1t} , are described by

(6.41) $\Delta y_{1t} = (b \cdot y_{2t} - b \cdot y_{1t}) \Delta t$.

Provided that sales of competitive products are assumed to die out exponentially according to the hypothesis'

(6.42) $\Delta y_{2t} = -b \cdot y_{2t} \Delta t$,

one obtains for small Δt and m=1 the type of trend curve described by eq. (6.38). The parameter τ describes the time which for t=0 has elapsed since the introduction of the product into the market.

The analytical trend curves discussed so far may in most cases be obtained as solutions to certain types of deterministic differential equations with underlying continuous hypotheses. In practice, these curves are fitted to historical data that have been measured discretely at constant time intervals using an unconditional least squares criterion. Attention should be given as to whether the stochastic disturbance u_t is added to the basically deterministic model (as was done for the example of Figure 6.10), or whether the model is multiplied by u_t or whether u_t shows up in the trend curve in a more complicated fashion. The least squares criterion and the results of an estimation may look very different for such cases.

ESTIMATION AND FORECASTING USING ECONOMETRIC MODELS

An econometric model today is understood

"to be an analytical representation of one or more statements about economic behavior, which representation relies upon statistical implementation for the purposes of hypothesis testing, parameter estimation, or use in prediction or simulation circumstances (Drymes, et al. [64, p. 291], viz. also Malinvaud [144]).

When formulating these statements, one tries to include as much a priori knowledge as one possesses about a possible functional form representing economic behavior, the sign, the order of magnitude and the

variability of a model's parameters and variables. Such knowledge may be obtained from micro- and macroeconomic theory, the behavioral sciences and - last, but certainly not least - by common sense and experimental experience. Essentially, here lies the main difference between the formulation, identification, estimation and validation of an econometric model and an uncritical application of classical correlation and regression analysis (viz. Box [22], Kuehn, Rohloff [131], Pierce [169], Chatfield [43]).

Unfortunately, the statements of economic theory are, in general, much too unspecific to allow directly the specification of a certain model. Therefore, perhaps, somewhat exaggeratedly, the econometrician has been compared with an alchemist who, by choosing an appropriate model describing unordered and non-experimental data, obtains "gold" or, what is relevant, significant results [131]. Drymes, et al.speak in this context of "Sherlock Holmes inference" [64]. However, although it is not altogether clear what a good econometric model is and how it should behave in a test battery, compared to other not quite as good models, one may say that a good econometric model should give a plausible and reasonably good description of real economic behavior. Using all the estimation and testing methods of econometry this then at least enables one to reject a great number of bad models (viz. Theil [199]).

In corporate modeling, economic statements are expressed in the form of equations. However, although the equations express statements about economic behavior, only such segments are modeled by econometric methods as contain, at least partially, stochastic disturbances to describe uncertainty and risk. By definition, econometric models are stochastic models, although they may contain deterministic relations or be used with expected values of variables and parameters. Typically, such equations describe relations and interdependencies between variables belonging not only to the firm's "inner environment" (Boulding), especially in the area of production and finance, but also to its external environment which is more open to stochastic influences and fluctuations. This happens especially in the marketing area, where stochastic effects due to the behavior of a great number of customers, suppliers or potential employees have to be taken into consideration. One may well say that especially the marketing processes connected with sales of relatively low priced consumer products in small quantities to a great number of households has

proven to be an interesting field for econometric analysis (e.g. [5,11, 83,93,132,154,155]). The coupling of a firm's variables to the variables of a national or international economy are also open to an econometric investigation, e.g. it was found that sales of CIBA-GEIGY dyestuffs in West Germany could be described as a function of the textile production index. Other econometric models were then constructed to model production orders and shipments of these products.

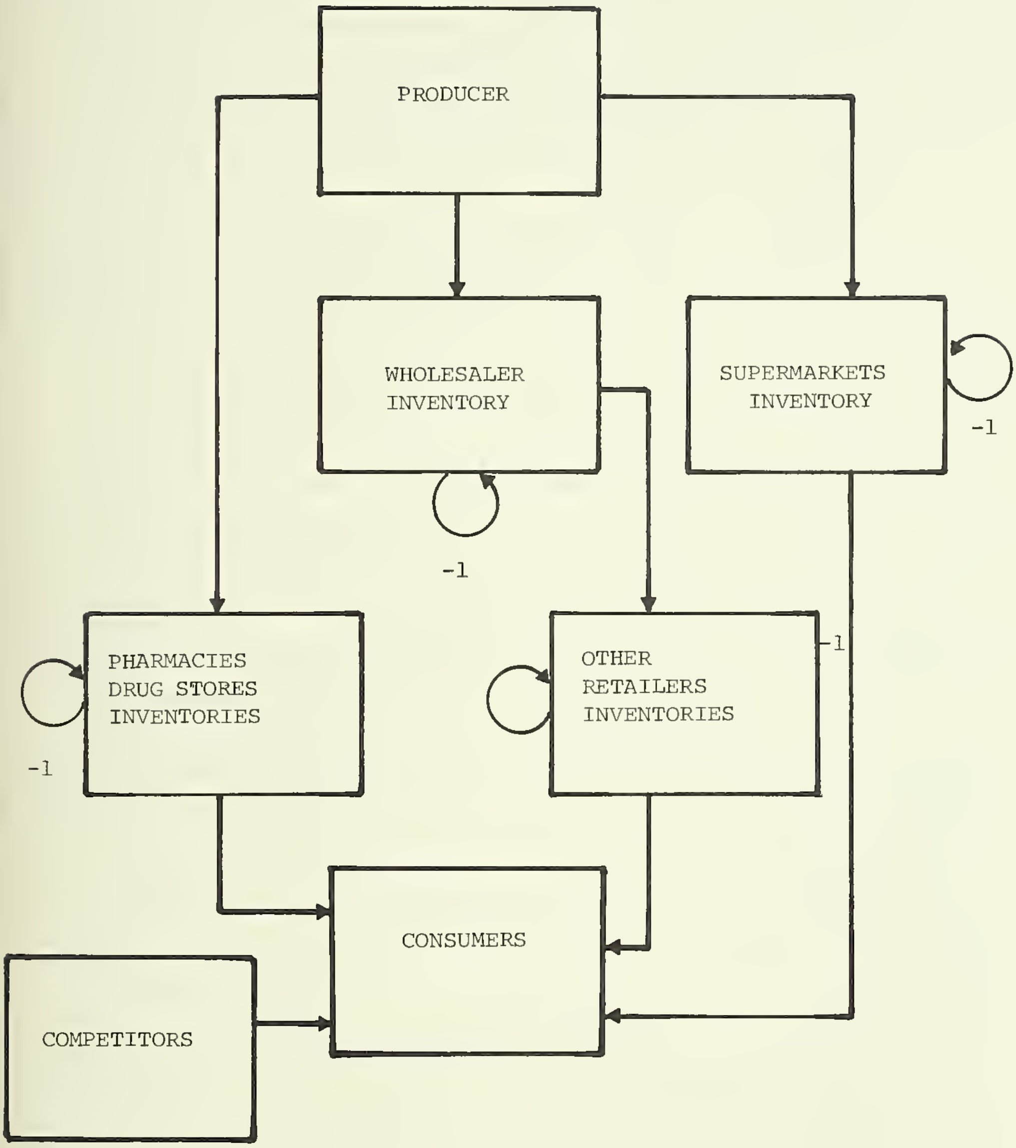
Also the short- to long-range descriptive models described in the previous two sections are essentially stochastic models. They may well be called econometric models, especially because they largely require the same identification, estimation and verification methods. But in the sequel, a narrower definition will be followed, calling econometric models only models that give an explanation of economic behavior via behavioral equations.

Marketing Example

In the following sections, some tentative models will be described that may possibly allow the description of the sales of a cosmetic product to a great number of households. For a more explicit description of such marketing processes, the interested reader is referred to Kotler [129], Montgomery, Urban [154] Parsons, Schultz[167], Meffert, Steffenhagen [149]. The examples are mainly intended to illustrate the use of econometric models in corporate modeling, their possibilities, problems and limitations. Similar and both partially successful and implemented models have been constructed at CIBA-GEIGY for a number of years. The Decision Calculus model discussed in chapter 5 is related to the same investigation.

It is assumed that the product is purchased by the consumers in supermarkets and in the retail business (pharmacies, drugstores and other retailers). A number of competitive products are distributed in the same fashion. A price competition exists between the products that expresses itself in price changes and various special offers. The product is purchased several times a year by a great number of households in several geographic regions. Figure 6.12 gives an impression of the material flow between producer and consumer. As one may see, direct sales from the producer to the consumer (purchases of firm employees in company stores) have been neglected. Hence, it has to be taken into consideration that

Figure 6.12. Material flow of marketing model



the material flow touches several intermediary deliverers and their inventories. This is indicated by self-loops in the graph. The firm may influence the consumer using different advertisement media and sales prices. This is possible directly by advertising via television or by direct mail, indirectly by supplying the intermediary deliverers with posters, samples and special discount offers. Appropriately scaled variables (values, impulses) would make up the decision variables of the firm.

Using measurements of exogenous variables (sales of competitors from sample data), decision variables and endogenous variables (e.g. sales by value, market share) the objectives underlying the construction of such a marketing submodel could be twofold. First, the relation between the decision variables of the firm and the endogenous variables is to be identified and estimated in order to possibly give an indication of a better media mix. Second, to adjust production to possible changes in demand, sales forecasts conditional on specific values of the exogenous and decision variables are to be generated (viz.[Theil 196, 197, pp. 6-42], Wold [216, pp. 5-36] for a more extensive classification). It should be noted that these two objectives are often likely to be incompatible: an econometric model with highly intercorrelated explanatory variables (e.g. collinear variables) may be very well suited to producing point forecasts, i.e. conditional forecasts of the expected values of the endogenous variables. But the interval forecasts and explanations it gives may be completely wrong. In contrast to this, a model could well supply explanations that are useful for decision making, but be inferior to the descriptive models previously discussed with respect to its forecasting properties.

Time Series versus Cross Sectional Approach (viz. e.g. Theil [199])

One of the endogenous variables of a model describing the marketing process of the product will very likely be market share or sales. These could be defined with respect to value or volume measurements.

Three reasons speak especially in favor of sales as an endogenous variable: the volume of the total market could, on one hand, be used as an either endogenous or exogenous variable in a sales model. In addition sales by volume or value are very often likely to be a target variable of a firm. Last, but not least, sales data may often easily be gathered from a firm's reporting and planning files. Models that use market share as endogenous variables very often do not possess these advantages

to the same extent. Measurements of market share are usually less accurate because the volume of the total market is often only known from consumer or producer panels. On the other hand, market shares may be well suited for modeling purposes if the volume of the total market exhibits seasonal or cyclical fluctuations that cannot be described in the model. Often it will be useful to construct both sales and market share models in order to establish compatible results. In the following discussion, sales by value will be used as an endogenous variable.

Another very important question that has to be answered before the construction of an econometric marketing model is undertaken, is whether a time-series model or a cross-sectional model or a mixture of these types should be chosen.

For the example given, one would relate variables that are defined with respect to location aspects in equations with a cross-sectional model. Hence, measurements of sales, advertisement expenditures and prices, e.g. in one month, but in different sales regions, or by different wholesalers and retailers would be used to estimate the model. In a time-series model, one would perhaps employ measurements of the same variables, but in one region and successive months for the same task.

Both types of models have their advantages and disadvantages. Ideally, one would combine the two approaches but this may prove incompatible because of data problems. One may, perhaps very cautiously, note that for the kind of problem described, time-series models have proven to be more reliable in practice than cross-sectional models. This is the case although one is likely to encounter methodological problems with time-series models which usually do not appear in cross-sectional models. There are two main reasons for this observation. First, it is extremely difficult to tidily define a large number, say 20, of sales regions. One may well think of cases in which advertisement media, like journal or television advertisement, influence customers in several regions. As a consequence, one would have to deal with location carry over effects, quite apart from the fact that one could not deal with time carry over effects. Second, one assumes in a cross-sectional model that the estimated parameters of the model are valid for all the sales regions. Especially variables of a demographic-geographic nature for which no measurements are available may produce severe equation errors if they have different effects in different regions.

Of course, the corresponding objections hold for a time series model as well. One assumes that essentially one model and set of parameters holds for the time interval under investigation. This certainly is a dangerous hypothesis in a time of rapid changes of consumer taste, frequent introduction of competitor products into the market and changing style and strategy of competitor advertising. However, practical work with econometric models seems to suggest that with a time-series model, it is easier to overcome these difficulties.

One of the main methodological difficulties usually encountered with time-series models arises from the positive autocorrelation of the time-series. This is very often due to time trends, conjuncture cycles and seasonalities. The series shown in Figure 2.5 is a typical example and the periodogram of Figure 2.6 is representative for the general behavior of a great many economic time series. With the Box-Jenkins models discussed in the previous sections, appropriate functional transformations and differencing was used to eliminate this sort of non-stationarity. If similar techniques are not applied to econometric models, one often obtains a positive autocorrelation of the stochastic disturbances u_t in an estimated model and as a consequence the variances of the parameter estimates may be grossly underestimated. However, econometric theory today supplies a number of techniques to deal with this sort of problem practically. Some indications will be given below.

The Linear Model and Assumptions

The simplest econometric time series model that one could use to describe sales of the consumer product would be to explain sales y_{1t} of a product in an aggregated manner directly as a linear function of the decision variables and exogenous variables. This would give

$$(6.43) \qquad y_{1t} = a_0 + \sum_{i=1}^{4} a_i\, \Theta_{it} + a_5 \cdot x_{1t} + u_t \quad ,$$

where Θ_{1t} denotes product price, Θ_{2t} expenditures for television advertising, Θ_{3t} direct mail and Θ_{4t} expenditures for posters, samples and special discount offers; the exogenous variable x_{1t} would denote sales of competitor products and u_t the residual scatter in y_{1t} that cannot be explained by these variables. The coefficients a_j, $j =[1,5]$, weigh the influence that different variables have on sales, the so-called intercept a_0 would be used to express a constant level of sales that cannot be influenced by the decision and exogenous variables. Obviously,

a trend or a seasonality is not taken care of in the model eq. (6.43).

Single equation linear models, as expressed by eq. (6.43) are the best understood models in econometrics. They are usually estimated by ordinary least squares (OLS), i.e. one determines the parameter values a_j, $j = [1,5]$ directly in such a way that

$$(6.44) \qquad S = \sum_{t=1}^{n} u_t^2 \rightarrow \text{Min.}$$

One obtains thus so called best-linear-unbiased estimates (BLUE) of the parameters and the variance of u_t provided that the assumptions that the residuals have zero expectation, a constant, i.e. not time dependent, variance σ^2 and zero covariances are fulfilled. This may be expressed by

$$(6.45) \qquad \begin{aligned} &\varepsilon\{u_t\} = 0 \\ &\varepsilon\{u_t^2\} = \sigma^2 \quad t = [1,n] \\ &\varepsilon\{u_t u_t\} = 0 \quad t \neq t', \ t' = [1,n] \ . \end{aligned}$$

In addition it is required that the explanatory variables be uncorrelated with the disturbances and be linearily independent among themselves. All measurements of right hand side variables must be regarded as "fixed numbers." Also there should be enough measurements for every model variable, say, as a rule of thumb, seven for every paramater to be estimated.

Employing the parametric hypothesis that the u_t are normally distributed, allows one to construct confidence intervals for the parameters and predictions and perform hypothesis testing for single or groups of parameters using Student's t-test and the F-test (viz. econometrics textbooks Johnston [122], Dhrymes [65], Theil [199]). The concept of confidence intervals and regions is very important for the problem used as an illustration in this chapter. It allows one to test the hypothesis that a certain variable or group of variables have no significant impact on sales, or that certain variables have a stronger influence than other variables. This is of importance, whenever one tries to establish statements about the absolute or relative effectiveness of advertisement media on sales. The same is true in the case that one tries to quantify the risk in a sales forecast connected with certain advertising decisions and values of the exogenous variables.

Although one might imagine exceptions, one will ask the parameters for the given example to obey the restrictions a_1, a_5<0 and a_2, a_3, >0 a_4>0. This is a plausible conclusion if one excludes that increases in

sales price and competitor sales have a positive effect, advertisement expenditures a negative effect on sales of the product described.

Since an unrestricted estimation method is used in most applications, and because the parameters themselves may be understood as random variables, one has, more correctly, to ask the probability to be rather low that these a priori restrictions are violated. Similar plausbility checks are carried out with practically all econometric models. If a model fails such checks, it has to be reformulated.

Because an econometric model in practice very often does not fulfil the assumptions made for the general linear model, econometric literature to a large extent deals with deviations from these very assumptions. Mainly two lines of attack are chosen to treat such deviations in practice: either appropriate variable differencing and functional transformations are used to bring the general model into a form that fulfills the assumptions of the general linear model or, one uses extended estimation methods. The inspection of the graphs of the time series involved and graphs of the autocorrelation function or periodogram of the residulas u_t of a fitted model suggest what kind of variable differencing and transformation should be used (Durbin [68,69], Box, Pierce [24], Malinvaud [144, pp. 440-503]).

Differencing and Transformation

At the level of the heavily aggregated model, as expressed by eq. (6.43), one could specify a great number of different linear models that are compatible with economic theory and a priori knowledge. For example, the model

$$\nabla y_{1t} = a_0 + \sum_{i=1}^{4} a_i \, \nabla\Theta_{it} + a_5 \cdot \nabla x_{1t} + u_t \tag{6.46}$$

is linear in the model parameters and explains sales differences in two successive periods as a function of the differences in the decision and exogenous variables. Such a model would typically be used to eliminate a linear trend. Without further statistical testing, one could have also formulated a model that describes relative changes in sales as a function of relative changes in the explanatory variables or models that assume neither quite as strong an autocorrelation of the series as in eq. (6.46) nor a regular pattern of the autocorrelation function of u_t. In analogy to Box-Jenkins models, one would employ the lag or time shift

operator to specify such models and make them accessible to OLS estimation (Cochrane, Orcutt [50]).

Often functional transformations like the logarithmic, inverse or square root transformation help one to fulfil the assumptions made for the general linear model. A multiplicative model

$$(6.47) \qquad y_{1t} = a_0 \cdot \prod_{i=1}^{4} \Theta_{i,t}^{a_i} \cdot x_{1t}^{a_5} \cdot u_t$$

could be reduced to a linear model using the transformation $y_{1t}^{*} = \ln y_{1t}$. One would have to assume that $\ln u_t$ fulfills eq. (6.45) and is normally distributed. This hypothesis would typically be tested for problems in which the amplitudes of random fluctuation seem to be directly proportional to the product of the levels of the explanatory variables. Box, Cox [21] and Box, Jenkins [23, pp.496-497] have suggested a transformation formula and evaluation procedure for a wide class of functional transformations. It is described by

$$(6.48) \qquad y_{1t}^{*} = \begin{cases} (y_{1t} + \lambda_2)^{\lambda_1} & \lambda_1 \neq 0 \\ & y_{1t} > -\lambda_2, \\ \ln (y_{1t} + \lambda_2) & \lambda_1 = 0 \end{cases}$$

and incorporates the logarithmic ($\lambda_1 = \lambda_2 = 0$), inverse ($\lambda_2 = 0$, $\lambda_1 = -1$) and square root transformation ($\lambda_2 = 0$, $\lambda_1 = 1/2$); λ_1 , λ_2 are fitting parameters. Such a transformation formula may easily be implemented as a module in a CSPS.

Nonlinear Models

If prior knowledge or experience gained in the model verification step indicates that linear or so-called intrinsicly linear models are not justified, one will start to experiment with models that are nonlinear in the parameters. So one could imagine that the assumption of a multiplicative coupling of competitor sales x_t and advertisement expenditures Θ_{jt}, $j = [2,4]$ or sales prices Θ_{1t} is not justified. Instead, one would perhaps try to estimate the model

$$(6.49) \qquad y_{1t} = a_0 \prod_{i=1}^{4} \Theta_{it}^{a_i} + a_5 \cdot x_{1t} + u_t \quad .$$

The functional form of this model does not look more complicated than for the previous models. However, since the model at the same time contains additive and multiplicative terms, it may not be transformed into

a model that is linear in the parameters. Such models have to be estimated by a nonlinear least squares method (viz. Marquardt [145], Box-Jenkins [23, pp. 504-505], Späth [192]) or more generally by maximum-likelihood estimation (viz. Goldfeld, Quandt [90]). It goes without saying, that a linear or intrinsicly linear model should only be understood as a crude description of actually non-linear economic phenomena. Such a model is mainly chosen for estimation convenience. Practical experience suggests that an approximation is the more unrealistic, the more the values of the model variables vary or, equivalently, the more one models at a micro-level instead at an aggregated level.

Distributed Lags

In the discussion it has so far been completely neglected that advertising expenditures do not necessarily lead to instantaneous changes in sales. An inspection of the material flows shown in Figure 6.12 indicates that time delays between the purchase decisions of the customers and their recording as sales in the firm's sales statistics are likely to appear whenever the time base of the model (i.e. months) is smaller or of the same order of magnitude as the material flow times. If one in addition, takes into account that purchase decisions of the consumers are brought about by past and current advertising expenditures, one would expect that advertisement impulses effect sales in several and delayed time periods. Such effects could be described by the aggregated distributed-lag model

$$(6.50) \qquad y_{1t} = a_0 + a_1 \cdot \Theta_{1t} + \sum_{i=2}^{4} \sum_{j=0}^{j_{max}} a_{ij} \Theta_{i(t-j)} + a_5 x_{1t} + u_t ,$$

where the coefficients a_{ij} now indicate that the advertising series show up in the model with several and by $j=[0,j_{max}]$ delayed terms. Figure 2.4 illustrates such distributed lag effects. Figure 6.13 shows the results of a linear distributed lag model, as have been used for a great many econometric investigations at CIBA-GEIGY. The sales price was not considered to be a decision variable in the model, because it was held constant over the period of observation (n = 36 monthly measurements). The intercept a_0 and other parameters and variables were eliminated in a stepwise regression procedure [48,175,177]. Figure 6.13 shows a graph comparing sales measurements and sales values generated by the model, the estimated regression coefficients, an average time lag of the variables

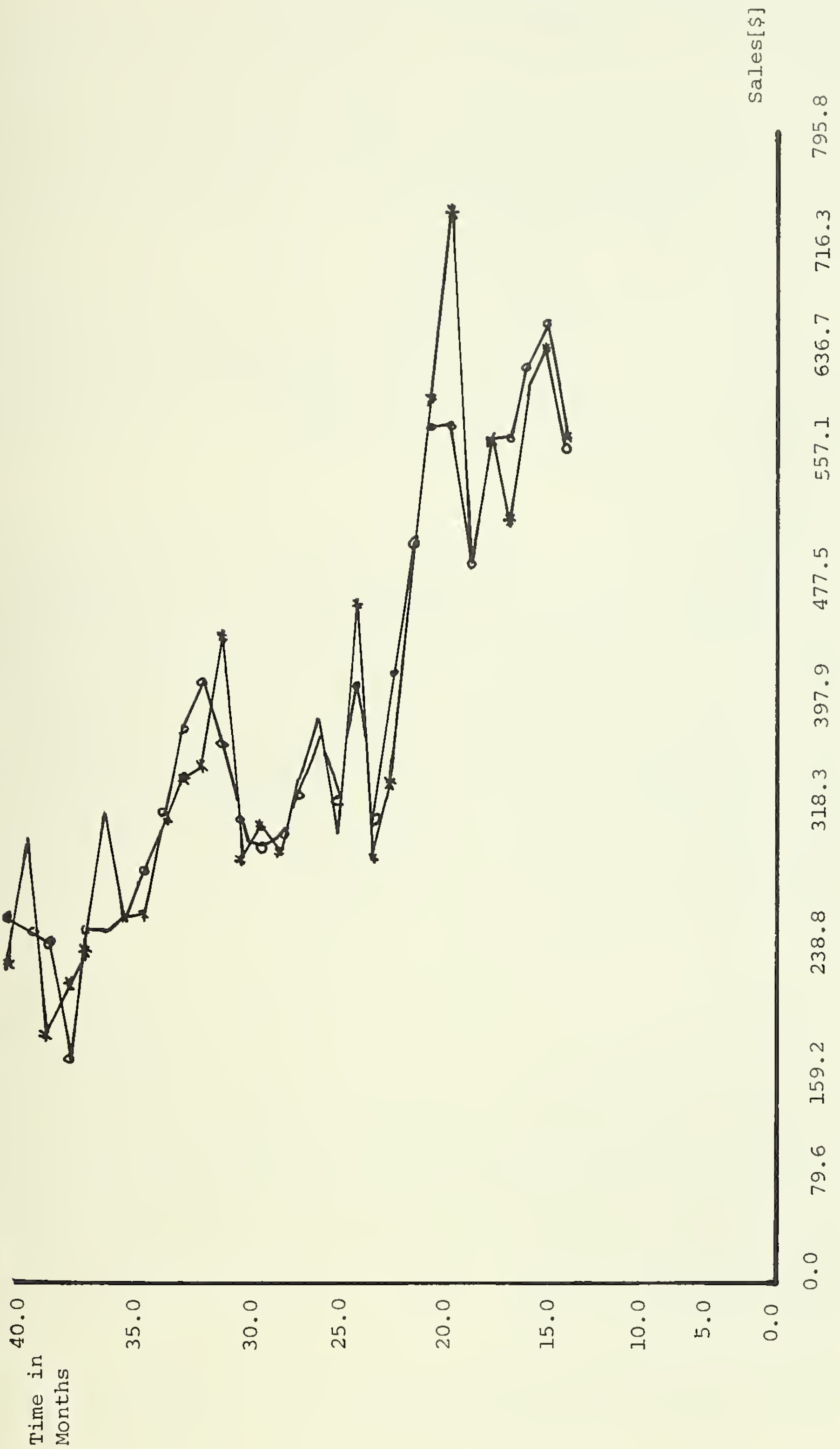


Figure 6.13. Results of a distributed lag advertising model.

and the results of some significance testing. The average time lag corresponds to the expected value of a triangular distribution of the lag parameters a_{ij} (viz. de Leeuw [59], Rosenkranz [178,180]). Not competitor sales, but a proxy variable, the values of which correspond to the number of introductions per month of competitor products into the market, was chosen as an exogenous variable.

Econometric theory nowadays supplies a number of approaches and techniques by which the coefficients of distributed-lag models may be determined. Chapter 9 contains an actual application of distributed-lags at CIBA-GEIGY as well as additional references.

Simultaneous Equations

The models so far described have not taken a possible interaction between the model variables into consideration. Such an interaction could arise from the process by which an allocation of advertisement by expenditures to different media is effected. Normally, this is done by product managers and members of the marketing department of the firm. Their decisions may be influenced by sales in the previous period $y_{1(t-1)}$ and, provided that the time base of the model is large enough, by reports on sales y_{1t} in the same period. Assume that the firm is willing to spend an amount y_{2t} on advertising according to the hypothesis

$$(y_{2t} - \Theta_{5t}) = b_0+b_1 \cdot y_{1t} + b_2\, y_{1(t-1)} + v_t \tag{6.51}$$

The coefficients b_j, $j = [0,2]$, denote the parameters of the model, v_t a stochastic disturbance and Θ_{5t} the part of the advertisement budget not determined from current or previous sales values. Note that y_{1t} and y_{2t} are both endogenous variables that interact. It can no longer be distinguished in the model, whether the level of the advertisement budget is due to the level of current sales or whether a sales level is due to the advertisement level: both interact. Now the advertising budget y_{2t} is distributed with complete certainty on the different media. This results in the identity

$$y_{2t} = \Theta_{2t} + \Theta_{3t} = \Theta_{4t} \quad . \tag{6.52}$$

Elimination of one of the decision variables, say Θ_{4t}, in eq. (6.43) then results in

$$y_{1t} = a_0 + \sum_{i=1}^{3} a_i \, \Theta_{it} + a_4 \, (y_{2t} - \Theta_{2t} - \Theta_{3t}) + a_5 \, x_{1t} + u_t \tag{6.53}$$

and another simultaneous model equation. An OLS estimation of either eq. (6.51) or eq. (6.53) would lead to biased estimates either because y_{1t} depends on v_t or y_{2t} depends of u_t. Econometric theory provides a number of techniques that allow the estimation of the parameters in simultaneous equations such as two stage least squares (2SLS), three stage least squares (3SLS), full information maximum likelihood (FML) or fixed point estimation (FP) (viz. econometrics textbooks Johnston [122, pp. 231-295], Malinvaud [144, pp. 597-722], Mosbaeck, Wold [157]). In the present example, a further difficulty could arise, because a lagged endogenous variable or predetermined variable $y_{1(t-1)}$ is also contained in the model. A correction of the time-series employed using techniques developed by Cochrane, Orcutt [50] could be carried out before the parameters of the simultaneous equations are estimated (viz. also Chow [45], Fair [75], Godfrey [88]).

Frequently, one obtains systems of coupled model equations if marketing phenomena are described more explicitly on a microlevel. Provided that the corresponding graph does not contain loops of zero length, one may order the equations of the model in such a way that a recursive OLS estimation of the model parameters is possible. Notably, Wold [216] has dealt with such models. If such a recursive estimation is not possible, one has to resort to the techniques mentioned above.

Auxiliary Variables

For the given example, sales would be recorded whenever products are delivered to supermarkets and wholesalers. Therefore, their time pattern is mainly determined by the sales expectations and inventory policy of the supermarkets, wholesalers, pharmacies and retailers (viz. Figure 6.12). Also announced price changes would probably have sales effects, because the firm's intermediary customers would for example try to fill up their inventories before a price increase is in effect. Usually the firm's intermediary customers will not carry out an inventory optimization. This would require that they determine optimal order quantities and order schedules based on their sales forecasts, inventory and ordering costs.

But they will have security stocks and reorder often in a more or less regular time pattern. This may cause difficulties if one wanted to relate e.g. weekly advertisement expenditures with weekly sales, because orders could show a biweekly periodicity.

A more detailed description of the laws governing the marketing process assumed could well lead to a large number of equations, variables and parameters. Some of the variables could be measurable, but incorporate a large measurement error, for others it could be impossible to obtain measurements. However, one would still want to estimate such a model. The use of dummy, instrumental or proxy variables sometimes makes such problems accessible to econometric estimation.

Assume that it takes the firm τ time units to process an order. Then it would record sales as

$$(6.54) \qquad y_{1t} = \sum_i yos_{i(t-\tau)} + \sum_j yow_{j(t-\tau)} \quad ,$$

where yos_{it} denotes orders of supermarket i in period t and yow_{jt} orders of wholesaler number j in period t. If one concentrates on the formultation of the microstructure for the supermarkets, one would possibly obtain the following structural equations. The inventory level by quantity yin_{it} of supermarket i would be described by $(t = [1,n])$

$$(6.55) \qquad yin_{it} = yin_{i(t-1)} + \frac{yos_{i(t-\tau)}}{\Theta_{1(t-\tau)}} - \frac{ys_{it}}{yp_{it}} \quad .$$

This equation holds if one assumes that delivery times are small compared to the time base of the model; ys_{it} would denote sales by value in period t, yp_{it} the sales price determined by supermarket i and Θ_{1t} the sales price of the firm. Given an initial inventory level, yin_{io}, this equation could be written in the form

$$(6.56) \qquad yin_{it} = yin_{io} + \sum_{t'=1}^{t} \left(\frac{yos_{i(t'-\tau)}}{\Theta_1(t'-\tau)} - \frac{ys_{it'}}{yp_{it'}} \right) \quad .$$

To describe sales ys_{it}, a model similar to eq. (6.43) could be used:

$$(6.57) \qquad ys_{it} = a_{0i} + a_{1i} \cdot yp_{it} + \sum_{j=2}^{4} a_{ji}\, \Theta_{jt} + a_{5i}\, x_{1t} + u_{it} \quad .$$

The inventory policy of the supermarkets would have to be taken care of in the structural equation that describes orders yos_{it} of supermarket i in period t. Assume that an order in period t is only placed provided that the inventory level in the previous period was below the security

stock yin_{i0} i.e. $yin_{i(t-1)} < yin_{i0}$. Introducing a (0,1) dummy variable yd_{it} defined by

$$(6.58) \qquad yd_{it} = \begin{cases} 1 & yin_{i(t-1)} < yin_{i0} \\ 0 & \text{else} \end{cases}$$

could lead to the following multiplicative model for yos_{it}:

$$(6.59) \qquad yos_{it} = b_{0i} \cdot ys_{i(t-1)}^{b_{1i}} \cdot \Theta_{it}^{b_{2i}} \cdot \Theta_{4t}^{b_{3i}} \cdot yd_{it}^{b_{4i}} \cdot v_{it} \ .$$

The variable v_{it} would again be a stochastic disturbance. Only Θ_{1t} and Θ_{4t} are contained in the model, because it was assumed that only these decisions directly effect orders of the supermarkets. The model is well suited to express that orders are only placed provided that the inventory level has fallen beneath the security stock.

Unobservable Variables (viz. Theil [199], Griliches [98])

In many instances, the inventory level and security stock of the supermarkets would not directly be measurable. Mere guesses of yd_{it} would probably incorporate large measurement errors and lead to biased estimates. The problem may be circumvented, however, if one is able to substitute the unknown or inaccurate variable by another so-called instrumental variable. This variable should be highly correlated with the true original variable, but uncorrelated with its measurement errors.

For the example given

$$(6.60) \qquad yd_{it} = \begin{cases} 1 & yos_{it} > 0 \\ 0 & yos_{it} = 0 \end{cases}$$

could be such a substitute. It should be noted that the instrumental variable estimation as has been briefly described above very much resembles some problems encountered with the estimation of simultaneous equations, e.g. 2SLS estimation may be viewed as a special instrumental variable estimation.

Aggregated and Disaggregated Models

Eqns. (6.54 - 6.60) give an indication of how econometric models may be specified and estimated on a micro-level. The description was, however, incomplete, because equations were formulated for the supermarket segment only. For a more complete description, equations describing orders and sales of wholesalers, pharmacies, other retailers and, last but not least, the consumers would have to be specified and estimated. If one assumes that the necessary data for such a micro-model are available, the question arises at once whether the results obtained from an aggregation of the micro-models would be compatible with the results obtained directly from an estimation of an aggregated model as is expressed by eq. (6.43) or eq. (6.50). A substitution of eqns. (6.57) and (6.59) into eq. (6.54) at once establishes that there should be some form of correspondence. However, from the substitution it becomes immediately clear that the marco-model would contain non-linearities, interacting model variables, measurement errors, several stochastic disturbances, in short, all the stumbling blocks that make a direct OLS estimation of the aggregated model highly questionable.

Still, estimation problems are likely to exist with aggregated models. Especially the problem of omitted "latent variables" that are highly correlated with explanatory variables used in the macro-model may often lead to incorrect conclusions, i.e. conclusions that are not consistent with a sound micro-theory (Box [22]).The only tidy way to deal with such difficulties would be to carry out planned experiments with the real system.

Forecasting

Very often, econometric models will be used not only for explicative, but also for predicative purposes. This may be the case if some historical measurements of the variables are excluded from the estimation and if they are used in a validation of a model's forecasting performance (retrospective or ex-post predictions). Alternatively, one uses ex-ante or prospective forecasting to generate expected values or confidence

intervals of the endogenous variables for a future time interval. In both cases, such forecasts will be based on the information available from the estimation step, especially on the parameter estimates and their estimated variance-covariance matrix.

In a situation in which an econometric model contains endogenous and decision variables only, there would not be a great difference between prospective and retrospective forecasting. Provided that the values of the the decision variables used in the forecast are actually taken by the firm's management, they would be known with the same certainty as competitive sales in the given example. Larger discrepancies are likely to arise because prospective predictions are conditionally based on values of the exogenous variables that have to be forecasted themselves. This will tend to widen the confidence interval of a forecast (viz. e.g. Feldstein [77]).

Criticism and Advanced Techniques

It has been noted before that hypotheses and statements of micro-and macro-economic theory are rarely available in a form which directly permits the specification of formal models. In practice, econometricians therefore assume models of economic behavior which are consistent with economic theory, but the exact specification is determined by trial and error incorporating all a priori knowledge, experience and intuition the model builders possess. Given the raw data, it is not surprising to observe that different model builders may derive entirely different, but plausible models.

Especially Box, Jenkins and their coworkers have in this situation advocated a philosophically and also methodologically different modeling approach (viz. [23,169,170,103]). They propose that economic laws should not be assumed a priori but be determined only after one has tried to explain the development of model variables on the basis of their past behavior and random disturbances alone. Especially Pierce [169] notes that the development of economic time series may on this basis very often be satisfactory or even better be described than by assuming specific laws between different model variables.

Instead of using multiple regression estimation techniques and the "fixed number" assumption mentioned with eq. (6.45), these authors propose a maximum likelihood estimation approach which fully takes the stochastic

properties of all model variables into account [206,214,23]. Univariate Box-Jenkins models as described by eq. (6.20) form the basis of the extended analysis. Let

$$(6.61)\quad \Theta_1(B)^{-1} \cdot \emptyset_1(B)\, \nabla^{d_1} y_{it} = u_{it}$$

and

$$\Theta_2(B)^{-1} \cdot \emptyset_2(B)\, \nabla^{d_2} y_{2t} = u_{2t}$$

be the ARIMA models obtained for two variables or time series y_{1t}, y_{2t} by the identification and estimation process briefly described earlier. The random variables u_{1t} and u_{2t} describe the behavior of y_{1y} and y_{2t} which cannot be described on the basis of their historical development. Box, Haugh, and Pierce [103,170] propose to test for causal relations between y_{1t} and y_{2t} using the estimated cross-correlation function of the estimated random disturbances u_{1t}, u_{2t}, e.g.

$$(6.62)\quad r_{12}(k) = \frac{\sum_{t=1}^{n-k} u_{1t} \cdot u_{2\,(t+k)}}{\left(\sum_{t=1}^{n} u_{1t}^2 \cdot \sum_{t=1}^{n} u_{2t}^2\right)^{1/2}}$$

for k = 0,1,2 ... and

$$(6.63)\quad r_{12}(k) = \frac{\sum_{t=1}^{n+k} u_{2t} \cdot u_{1(t-k)}}{\left(\sum_{t=1}^{n} u_{1t}^2 \cdot \sum_{t=1}^{n} u_{2t}^2\right)^{1/2}}$$

for k = -1, -2, ... and its approximate standard error. Pierce and Haugh [170, p.276] distinguish different types of causal relationships which may be identified by such an analysis. If for example $r_{12}(k)$ is significantly different from zero only for $k>0$, then y_{1t} is seen as the cause of changes in y_{2t}, for $k<0$ y_{2t} causes changes in y_{1t}. The case where $r_{12}(0)$ is significantly different from zero indicates a simultaneous interaction between the variables. Such two variable investigations may then form the basis for the specification and estimation of recursive or simultaneous explicative Box-Jenkins models (viz. [23,92,105]). It should also be noted that Box and Tiao have extended the analysis to include the effects of qualitative variables similar to dummy variable analysis in classical econometrics [27].

It is too early to evaluate the properties of such extended identification and estimation methods (viz. Chatfield [43]). It should be noted that many degrees of freedom are lost by the "prewhitening analysis" described by eq. (6.61). The same ovservation holds for the identification based on eq. (6.62) and eq. (6.63). As a consequence, many measurements ($n > 50$) of the variables are required and only few model variables may be dealt with in a model so far.It is also not clear yet how the identification using the cross-correlation function performs for more than just two model variables. In addition, all the criticisms already given for univariate Box-Jenkins models still apply.

In total, the extended methods briefly described may be used for detailed investigations involving few variables and long time series. Appropriate software packages are already available and may be attached to a CSPS.

In the typical situation of many variables and few measurements, model builders still have to rely on classical econometric methods, if they do not want to give up explicative modeling altogether. It should also be noted that the identification of relationships between model variables using the cross-correlation function has long been in practice (viz. e.g. [180]). A macro to allow the calculation of cross-correlation functions and their confidence limits for appropriately transformed model variables should be contained in the modeling software of a CSPS.

Econometric Estimation Methods in a CSPS

In the previous sections, a marketing example was used to verbally explain the possible application of econometric models in corporate modeling. Such submodels will be constructed mainly for the marketing segment of a corporate model, and to a lesser extent, for the production and financial segments. While therefore some standard econometric models and estimation techniques should be available in a CSPS, care should be taken that they do not restrict the application of other model types and solution methods. Purely econometric or time series modeling systems do not fulfil the needs of corporate modeling. A CSPS should supply the data handling facilities, language statement, estimation methods and statistical tests to at least handle the following types of econometric models:

1. Linear and intrinsicly linear one-equation models incorporating

leads, lags or differences in all, notable in the endogenous variables. Statements, macro-instructions and subroutines of the CSPS should allow the specification of leads, lags, differences and averages for model variables. Variable transformations using transcendental functions and the Box-Cox formulas should be possible by the same means. Macros should be available to generate series as are needed for the estimation of different lag distributions.

Accurate procedures for the inversion of symmetric and positive definite matrices, based on such methods as the Cholesky decomposition or orthogonal transformations, are required for all estimation methods based on the least squares principle (viz. Lawson, Hanson [135]). The user should be able to modify the main diagonal of these matrices as is needed e.g. for ridge regressions [110,111,146] to be used with multi-collinear estimation problems.

2. Models consisting of either linear or intrinsicly linear systems of simultaneous equations. In most cases, CSPSs supply macros performing 2SLS estimation to handle such estimation problems. The same macros may be used for instrumental variable estimation as is needed to deal with unobservable variables, measurement errors in variables, and lagged endogenous variables.

3. Non-linear models consisting of one equation. Mostly macros based on the Marquardt-Levenberg algorithm [145,23] are available to estimate one equation models which are nonlinear in the parameters. In contrast, to the models mentioned above,nonlinear models may in general not be specified by only indicating the type of variables and estimation method to be used. The explicit formulation of model equations should be possible using either statements of the modeling language itself or the source language a CSPS is based on. A language interface is required in the latter case.

4. Non-standard models and estimation. It should be possible to attach more refined estimation methods for special investigations to the system. Again, interlanguage communication facilities are likely to be requested in this situation.

MODEL SOLUTION METHODS

A model solution normally corresponds to the determination of the endogenous variables for given model inputs. It has been noted before that, depending on the rank of a linear model's coefficient matrix, one may distinguish between exactly determined, underdetermined and overdetermined model solutions. The last two cases will be discussed more thoroughly in chapter 7. Since the discussion is restricted to numerical model solutions only, one has in all cases to deal with solutions of systems of linear or nonlinear algebraic equations. For under- or over-determined systems additional criteria have to be specified to allow a model solution. Apart from this difference all solutions are closely interrelated from a mathematical as well as computational viewpoint. To give an example of this computational interrelation: a model estimation normally corresponds to the solution of an overdetermined system of equations in the model parameters which is most frequently obtained using a least squares criterion.

A similar criterion may also be used to generate solutions for exactly determined or underdetermined systems. Assume that the model is expressed by

(6.64) $$f_i\ (\underline{Y}_t\ ,\ \underline{Y}_{t-1}\ ,\ \underline{S}_t\ ,\ \underline{\Theta}_t) = 0\ ,\ i = [1,m]\ ,\ t = [1,n]\ ,$$

then the endogenous variables $\underline{Y}_t$ could be directly determined from eq. (6.64) for exactly determined systems. But the same solution could be obtained from a minimization of

(6.65) $$S_t = \sum_{i=1}^{m} f_i^2$$

or

(6.66) $$S_t = \sum_{i=1}^{m} |f_i|$$

(viz. Collatz, Wetterling [5, pp.120-122]). At the same time, eqns. (6.65 - 6.66) could correspond to the objective function for the evaluation of either over- or underdetermined systems of equations.

As mentioned before, a CSPS should supply a number of robust and versatile methods to carry out such evaluations, if possible, within several steps of the model design procedure. Certainly, linear matrix

methods are the most important methods for this purpose. It seems to be very useful to either include matrix macro-statements in a corporate simulation language that effect a matrix addition, multiplication, transposition and inversion or to supply a language interface for appropriate subroutine calls.

SOLUTION AND EXTENDED ESTIMATION METHODS

Although it seems that statistical estimations of corporate models have so far mostly been carried out by linear multiple regression [58,8, 204,163], it should be noted that statistical or economic considerations may call for other estimation methods. Statistical properties of a model may result in neither unbiased nor consistent parameter estimates in which case maximum likelihood estimation could be preferable to linear or even nonlinear regression (e.g. equations containing several nonlinar stochastic disturbance). Also one may well imagine cases in which a priori knowledge leads to the formulation of equality or inequality restrictions between model parameters or variables or estimators are asked for which are robust with respect to outliers. This could render a direct minimization of the squared error sum impossible. An example would be the estimation of a firm's production function under the assumption that it only employs efficient factor combinations to produce its outputs. Restricted estimation is likely to necessitate the applications of Tschebycheff-approximations and mathematical programming techniques (viz. Malinvaud [144, pp. 617-620], Brockhoff [31, p.714], Collatz, Wetterling [51, pp. 120-142], Späth [192], Lawson, Hanson [135]). Other problems of this nature have been discussed by Bracken, McCormick [29, pp. 83-92], Judge, Takayama [134], Chapman and Fair [39], Hartley, et al. [102] and Smith [188]. Matt [147] and Griese, Matt [96] describe an estimation method in which weighted linear regression and linear programming are combined to select significant exogenous and decision variables in stochastic models, Rosenkranz [177] reports on a similar elimination procedure based on some results by Cochran [48]. Computer codes for linear and quadratic programming are today available and may, for small scale problems, be used in a CSPS both for model estimation and model optimization (e.g. Künzi, Tzchach, Zehnder [133], Lee [136, pp. 126-160]). The CIBA-GEIGY COMOS possesses macro instructions that enable one to specify such solutions.

NONLINEAR EQUATIONS

A very robust and perhaps the simplest solution method that may be used with exactly determined simultaneous models that are nonlinear in the variables is the Gauss-Seidel algorithm as has been described for economic applications by Evans [73]or Naylor [161, pp. 139-141]. It requires neither the calculation of function derivatives not any complicated mechanism to generate a sequence of trial solutions. It is assumed that eq. (6.64) may be written explicitly as

$$(6.67) \qquad y_{it} = g_i\ (\underline{Y}_t\ , \underline{Y}_{t-1}\ , \underline{X}_t\ , \underline{\Theta}_t\ )\ ,\ i = [1,m]$$

For given t all variables except the endogenous variables would be known. Iterations denoted by a number k start from given or estimated initial values $\underline{Y}_t^{(k)}$, k=0. Their substitution on the right hand side of eq. (6.67) yields new values $\underline{Y}_t^{(k+1)}$ according to

$$(6.68) \qquad y_{it}^{(k+1)} = g_i\ (\underline{Y}_t^{(k)}\ , \underline{Y}_{t-1}\ , \underline{X}_t\ , \underline{\Theta}_t)\ ,\ i = [1,m]\ .$$

Letting k: = k+1 a sequence of right hand side substitutions will result in values $\underline{Y}_t^{(1)}$, $\underline{Y}_t^{(2)}$, $\underline{Y}_t^{(3)}$ ... . Iterations may be terminated, if absolute or relative changes in the endogenous variables are smaller than a predefined error limit between two successive iterations.

The stability and rate of convergence of the basic method may be improved by a number of modifications. Instead of iterating as described in eq. (6.68), one may use the scheme

$$(6.69) \qquad \begin{aligned} Y_{1t}^{(k+1)} &= g_1\ (\underline{Y}_t^{(k)}\ , \underline{Y}_{t-1}\ , \underline{X}_t\ , \Theta_t) \\ Y_{2t}^{(k+1)} &= g_2\ (Y_{1t}^{(k+1)}\ , Y_{2t}^{(k)}\ , \dots\ Y_{mt}^{(k)}\ , \underline{Y}_{t-1}, \underline{X}_t\ , \Theta_t) \\ Y_{mt}^{(k+1)} &= g_m\ (Y_{1t}^{(k+1)}\ , Y_{2t}^{(k+1)}\ , \dots Y_{(m-1)}^{(k+1)}\ , Y_{mt}^{(k)}\ , \underline{Y}_{t-1}, \underline{X}_t, \Theta_t) \end{aligned}$$

to generate successive values of the endogenous variables. A sequencing of the model equations employing the van der Giessen algorithm [201] may also considerably improve the convergence properties of the Gauss-Seidel method.

A variety of other either searching or approximation methods is available for the solution of a system of nonlinear equations like eq. (6.64). The reader is referred to Wilde [210], Box, et al. [28], Hoffman, Hofman [112], and Himmelblau [109]. A model described in chapter 3 was

solved with a fast and robust version of the Regula Falsi [179]. Software incorporating these and similar methods are available from many sources and may easily be attached to a CSPS. Simple algorithms like the Gauss-Seidel method may even directly be coded in the corporate modeling and simulation langauge as has been done for the CIBA-GEIGY COMOS.

STOCHASTIC SIMULATIONS
(viz. Fishman Kiviat [79,80,81], Naylor [161],McCarthy[148],Kleijnen[126])

There is no fundamental difference between the methods used to obtain numeric solutions to deterministic corporate models as may be expressed by eq. (6.64) and stochastic corporate models as may be expressed by

$$(6.70) \quad f_i\,(\underline{Y}_t\,,\,\underline{Y}_{t-1}\,,\,\underline{X}_t\,,\,\underline{\Theta}_t\,,\,\underline{U}_t) = 0 \quad i = [1,m] \; t = [1,n]$$

Indeed, the main difference from a computational point of view arises from the fact that the number of solutions needed in a stochastic simulation of a corporate model is likely to be at least an order of magnitude larger than in a deterministic model. Given initial values $\underline{Y}_0$ of the endogenous variables, a deterministic solution would correspond to n successive solutions of eq. (6.64) substituting known values of $\underline{Y}_{t-1}$ and solving a system of algebraic equations. Essentially the same is done with solutions of stochastic models. Known values of the endogenous variables are substituted. The same happens with the stochastic disturbances $\underline{U}_t$ which are obtained from a suitable random number generator. But it depends now on the type of simulation to be performed, how often for a certain stage t = [1,n]such a solution has to be carried out.

RISK ANALYSIS EXAMPLE

Let

$$(6.71) \quad y_{1t} = y_{1(t-1)} + \frac{(y_{2t} - y_{3t})}{(1+i)^t} \quad ,$$

where $y_{10} = 0$, t = [1,n] , describe the net present value connected with an investment project. The variables y_{2t} and y_{3t} describe cash-inflows and outflows connected with the project, i is a known discount rate. Assume that cash-inflows and outflows y_{2t} and y_{3t} are determined

from previous values, price and production quantity decision Θ_{1t}, Θ_{2t} according to

$$(6.72) \quad y_{1t} = f_1 (y_{1t-1}, \Theta_{1t}, \Theta_{2t}, u_{1t})$$

$$y_{2t} = f_2 (y_{2t-1}, \Theta_{2t}, u_{2t})$$

For given y_{10}, y_{20} and known distributions of the random variables u_{1t}, u_{2t} one may calculate empirical distributions or distribution parameters for the y_{jt}, $j = [1,3]$. We have conducted simulation experiments using COMOS with a CIBA-GEIGY investment model similar to the one above. In the order of $k = 100$ solutions of the (more detailed) model structure indicated by eq. (6.71) and eq. (6.72) were required for $t = [1,10]$(years) to establish the empirical distribution function shown. Random numbers from subjectively estimated triangle distributions were used to describe the u_{1t}, u_{2t}. This allows the quantifaction of the risk associated with varying developments of cash-inflows and outflows. However, all the difficulties discussed in chapter 2 were encountered with the subjective estimation of the distributions.

SOME ESTIMATES

One may also calculate parameters of the distribution of the y_{1t}. Assume that one wants to determine the expected value of y_{1t} with a predefined accuracy ε. The arithmetic mean $\bar{y}_{1t}$

$$(6.73) \quad \bar{y}_{1t} = \frac{1}{k} \sum_{i=1}^{k} y_{1t}^{(i)} \; ; \quad t = [1,n] ,$$

is taken to be the estimate of its expected value, then

$$(6.74) \quad \bar{y}_{1t} \pm t_{\frac{\alpha}{2}, (k-1)} \cdot \frac{s_t}{\sqrt{k}} \; ; \quad t = [1,n]$$

would define a 100 $(1-\alpha)$ percent probability confidence interval for the expected value. In these equations k would denote the number of simulations, $y_{1t}^{(i)}$ the result from an individual simulation, $t_{\frac{\alpha}{2}, (k-1)}$ the value of the t-distribution at confidence level α, $(k-1)$ degrees of freedom, s_t the empirical standard deviation of the y_{1t} obtained from

$$(6.75) \quad s_t^2 = \frac{1}{k-1} \sum_{i=1}^{k} (y_{1t}^{(i)} - \overline{y_{1t}})^2 .$$

If one defines

$$(6.76) \qquad \varepsilon = t_{\frac{\alpha}{2},(k-1)} \cdot \frac{s_t}{\sqrt{k}}$$

as a measure of accuracy for the arithmetic mean, then one sees immediately that this accuracy will only be reached after

$$(6.77) \qquad k \approx t^2_{\frac{\alpha}{2}(k-1)} \cdot \frac{s_t^2}{\varepsilon^2}$$

replications of $y_{1t}^{(i)}$. Under the simplifying assumption that the s_t^2 are more or less equal for all $t = [1,n)]$, one may then expect a stochastic simulation to require about k times the computational effort of a deterministic solution or simulation. The assumption of independent measurements that underlies eqns. (6.74) to (6.75) will be fulfilled for the given example because the stochastic disturbances $\underline{U}_t$ in eq. (6.72) will normally be uncorrelated in any two solutions, say $i \neq j$, $i = [1,k]$, $j = [1,k]$. For $k > 30$, say, one could use $t_{\frac{\alpha}{2},(k-1)} \approx z_{\frac{\alpha}{2}}$, i.e. the appropriate values of the standardized normal distribution.

The example corresponds to what in the literature is usually called a cross-section simulation with n cross-sections. Typically no carry-over effects between different sections were dealt with, i.e. it was not investigated how the expected y_{1t} in period t depended on the distribution of $y_{1(t-1)}$ in period (t-1). Such properties are investigated by what is usually denoted as time-series simulation. Because the hypothesis of independent measurements for the given example would not hold due to the autocorrelation of the endogenous variables, other methods of parameter testing have to be used. If one assumes for example that successive values of y_{1t} are generated by a stationary but correlated stochastic process, then a confidence interval for expected sales over time could still be calculated according to eq. (6.74) by an appropriate reinterpretation of the parameters. The empirical standard deviations of the y_{1t}, however, could not be calculated according to

$$(6.78) \qquad s^2 = \frac{1}{n-1} \sum_{t=1}^{n} (y_{1t} - \bar{y}_1)^2, \text{ where}$$

$$(6.79) \qquad \bar{y}_1 = \frac{1}{n} \sum_{t=1}^{n} y_{1t} \qquad ,$$

but would have to be corrected upwards for positively correlated values of the y_{1t} (viz. Narasimham [158] , Fishman [82]). This would then necessitate an extended time horizon $T > n$ for the simulation, if the confidence interval for y_1 were to be determined with accuracy ε and n stages for uncorrelated values of y_{1t}. Alternatively one could determine $\bar{y}_1$ and s from several independent time paths of y_{1t} as in a cross-sectional simulation.

In any case for either cross-sectional or time-series stochastic simulations a greater computational effort will be necessary than for a deterministic solution or simulation. Care should be taken that a CSPS supplies effective solution methods for such purposes. In addition it should incorporate statements or macro-instructions that allow some ease in the generation of different random numbers. Naylor [161, pp. 381-405] and Naylor, Balintfy, Burdick, Chu [159, pp. 43-122] describe extensively different techniques of random number generation. Variance reduction techniques may be applied for a possible reduction of simulation runs (viz. e.t. Naylor [161], Kleijnen [126], Rosenkranz [179]).

MODEL TESTING AND VALIDATION

In chapter 1 the objectives of corporate modeling were defined as being both descriptive and normative: based on the available information a model is meant to describe a firm'sactivities over time and in different areas. Such a description should help a firm's management to investigate possible outcomes of quantitative as well as qualitative policies, before they are actually chosen in reality. Thus the model is supposed to indicate policies or values of the decision variables that in a way guarantee and possibly improve the firm's activities in the future.

Before any practical use of a model is made,it has to be tested and validated. The purpose of this model design step is to show well the output of a model meets the predefined objectives. As Mihram puts it "... the credibility of any modeling effort rests on concrete demonstrations that the resulting model represents reality [151, p. 17]". If one does not succeed in establishing a correspondence between model output and output of the real world system described, or if the discrepancies between the two exclude that the model output may serve as a substitute for the real output at least to some extent, then the model of the hypothese expressed in it are not to be trusted. Provided that the modeling efforts

are not given up altogether after such a result has been reached, one has to modify the model in one of the previous steps and carry out the following steps anew. The kind of discrepancy discovered to the largest extent determines how far back in the design procedure one has to start again. Clearly what Kuehn and Rohloff [131] have termed errors of the third kind are most severe deviations between model and reality: the output of a formally correct model does not match with the intended use of the model that has been specified in the first step.

VALIDATION AND MODEL DESIGN PROCEDURE

It should be noted that the introduction of a test and validating step within the model design procedure by no means forces the model builder to postpone all model testing and validating efforts until his complete model is mature enough to pass this step as a whole. Its introduction before the implementation step only indicates that a model or components of a model should go through some formal testing and validating before real world decisions are possibly based on the modeling results. In fact, testing and validating a model comprises a great number of definitional, mathematical and philosophical problems that relate to all stages of the design process (viz. Churchman [46]). One may even be tempted to say that this step controls the others once the objectives have been formulated. Also one could note that it is part of the specification of the intended use of a model to also define standards and tests which have to be met or passed in every modeling step.

During the collection and preparation of data for a corporate model, a model validation may be carried out by a great number of qualitative and quantitative methods. It would involve checks on data relevance, stability and accuracy. If certain criteria are not met, the data collection or measurement process would have to be redesigned. Quite similarily, a validation may take place whenever model variables, parameters and equations are defined and specified. One would qualitatively or quantitatively anwer such questions as "Are model variables relevant, meaningful, and measurable" or "Are functional relationships or hypotheses about them compatible with the a priori knowledge one has about them from experience or economic theory? Are they plausible and relevant with respect to the needs of the user?" The GESIFLO-analysis described in chapter 4 is essentially part of a model's validation. Loops of strictly positive length in

the graph indicate an error in the lag structure of the model equations. The application of graph analysis to the investigation of distributed lag effects between model variables and the calculation of sensitivities of variables using graph reduction rules may serve in a comparison of intended and actual model structure and would be part of what Fishman and Kiviat [81] or Mihram have termed model verification: "The determination of the rectitude of the completed model vis-a-vis its intended algorithmic structure [151, p. 18]" or Fagerstedt and Petterson call validating the operating characteristics of a model [74, p.78]. In the estimation, solution or simulation step one might test the signficance of certain model parameters statistically, look for possible instabilities in a model solution or test the distribution of a model variable which one obtains from repeated stochastic simulations against a distribution which one either expects on a priori grounds or which one has determined from real world data. Last, but not least, an implemented model's performance may be compared with the performance of the real system and if deviations do not stay below predefined standards, modifications of the implemented model might be necessary.

PRAGMATIC VALIDATION

Model testing and validation is not only influenced by the modeling steps, but also strongly depends on the nature of the real system described, the information available about its operation and the use made of it. The financial segment of a corporate model with a great number of identities and deterministic first order difference equations is validated in a completely different fashion from a linear programming model for the production segment or an econometric model for the marketing segment. It seems to be practically impossible to suggest an exhaustive list of tests applicable under such circumstances. However, although it is not clear what validating a model precisely means, it is generally accepted that it involves a comparison of a model's performance with the objectives underlying its construction and in most cases a comparison with the real system. For the comparisons one follows Churchman's pragmatic philosophy and compares what is possible, either from the point of view of methodology or other conditions such as the available time and the financial means. The pragmatic and probably most important validation criterion for a corporate model may be formulated as follows: A corporate model is valid if it is

consistent with the available data and if the user performs better employing the model than doing without or an alternative model (viz. also Howrey [119], Dhrymes et al. [64], Van Horn [203], Naylor and Finger [160]).

Predominantly informal tests and comparisons are used in practice to establish the validity of a CSPM. Of central importance is the establishment of the "face validity" of the model (viz. Hermann [106]). This involves a more qualitative comparison and appraisal of the model output by the model user based on his prior knowledge and subjective opinion about the real system. If either the model output corresponds to his intentions or i he is not able to distinguish any longer between the output of the model and the real system, face validity is assumed to be established. The latter, more formalized procedure has been called the Turing's test by a number of authors (viz. Van Horn [203, p. 242]). Face validity and model acceptance are closely interrelated, because the model user is not an impartial observer. If the model fulfills his needs he tends to accept its validity. This question has already been discussed in chapter 2. Larréché and Montgomery have supplied a framework of factors shown below which influence the acceptance of marketing models [134]. It is thought that basically the same factors are relevant for the acknowledgement of face validity for a CSPM.

1. Expected Value
   - Training
   - Savings
2. Initial Costs
   - Purchase
   - Development
   - Adaption
   - Initial Data Gathering
3. Structure of Model
   - Adaptability
   - Completeness
   - Ease of Testing
   - Ease of Understanding
   - Robustness
4. Usage Characteristics
   - Ease of Communication
   - Ease of Control
   - Input Volume

- Response Time
- Running Costs

5. Usage Context
   - Type of Problem
   - Frequency of Use
   - Importance of Problem Described
   - Level of User
   - Number of Users

6. Validation History
   - Parameter Validation
   - Structure Validation
   - History of Successful Use

It is clearly seen that only the last factor refers to the model versus real world behavior comparison described above. The other factors are of an organizational, behavioral and technical nature and define the environment in which such a comparison may be carried out.

The comparison of an economic model, like a CSPM, with reality poses fundamental problems, because in general any experimentation with the real system is out of the question. Data and measurements are unplanned and as Pierce notes "... the economy is a miserable experimental design [169, p.20]". If measured values of the model variables exist at all, these same values of the variables are used throughout the modeling steps and model revisions and as Howrey concludes

"... the final result is a model that depends on both prior specification and data analysis and the extent to which the revised model is "confirmed" by the same data is difficult to determine" [119, p. 11].

This is an especially severe problem in cases in which one deals with models that contain decision variables: Historical measurement values correspond to one set of values of the decision variables and clearly hypothese about the effect of different settings of these variables cannot be validated from historical data [160, 161, p. 158]. Prospective predictions would therefore be necessary to validate hypotheses about different settings of the decision variables. But since only one set of possible values is actually taken, nothing can be said about the model's ability to predict the outcome of alternative policies.

STATISTICAL SPECIFICATION TESTING

Quantitative tests to establish whether a model is consistent with the available data or incorrectly specified are great in number. Most of these tests are parametric, i.e. special statistical assumptions about the distributions of stochastic disturbances and parameters are implied. Especially the econometric literature provides tests that allow one to verify hypoteses regarding

1. the significance of single parameters, of groups of parameters and especially of linear relations between parameters

or to detect a wrong specification of a model as might result from

2. omitted variables in a relation,
3. an incorrect functional form of a stochastic model equation,
4. a neglected simultaneity of model variables,
5. time dependent stochastic disturbances,
6. auto-correlated disturbances,
7. non-normal disturbances.

Errors and tests related to misspecifications have especially been investigated by Ramsey [172,173,174], specification error tests have been formulated by Durbin [56,57,166]. Other errors are quite extensively discussed in econometric textbooks. An extensive survey of the state of the art has been given by Dhrymes et.al. [64]. Frequently the intercorrelation of timeseries in models of the distributed-lag type poses serious estimateion problems. A qualitative application of the tests described by Farrar and Glauber [76, 208] have been found helpful in a number of instar ces [178, 180]. Some tests on the hypothesis that data not used in the model esimation are consistent with an estimated model are described in the literature (viz. Johnston [122, pp. 131-138], Howrey [119, pp. 7-10], Box-Jenkins [23, pp. 126-170]) and form the basis for the construction of confidence intervals and regions for forecasts of the model variables. Hsu and Hunter have proposed to compare Box-Jenkins models of the real and simulated data for a validation [121].

Although specification testing is certainly very useful in the elimir ation of a great number of possible hypotheses and models from further investigation, some of its limitations should also be mentioned: First, parametric statistical tests of model misspecification are in general based on statistical assumptions regarding the nature of the real system. As such they are open to validation themselves. Second, if several

misspecifications in a model have occurred simultaneously, this is extremely difficult to establish by specification-testing. Third, in some cases one obtains several models or conflicting hypotheses that are compatible with the available data.Also different models might fail different tests. Finally, it has to be taken into account that the probability of type one errors (a correctly specified model fails in a number of tests) and type two errors (an incorrect model passes a number of tests) increases with the number of tests performed. In all cases it can be extremely difficult to assess which model should be selected or along which lines further investigations and model revisions should be carried out [64, 119, 190].

Nevertheless specification testing plays a central role in practical model validation and can not possibly be omitted with corporate models that rely on statistical data. Some of the standard specification tests for econometric models should be included in a CSPS. Care should be taken that more specific tests may easily be attached to the system whenever necessary.

While the corporate modeling literature supplies a lot of evidence that the face validity of most models was established before they were implemented, relatively few examples are known in which specification testing was used. Perhaps the best documented model in this respect is Aurich's model of a German textile company [8], but a number of other articles also describe the combination of estimation with multiple regression techniques and specification testing (viz. Wagle [264], Naylor [163], Rosenkranz [178, 180] , Davis et al. [58]).

Not much is known about the comparison of different models using statistical tests with estimation samples or post-sample observations. Econometric textbooks supply tests for comparing alternative models of the general linear model type essentially testing whether certain linear combinations of regression coefficients are significantly different from zero. Rosenkranz has used such test in a stepwise regression sense [177] and in a more general application [180]. These tests were not fully integrated into the CIBA-GEIGY COMOS, but were performed in connection with the significance testing of marketing models. Drymes et al. and Howrey have described more general tests, notably by Aitchison-Silvey [2] and Cox [52, 53] using tests on estimation samples, or Williams [212, 119] on post-sample observations. Howrey gives further indications of how Bayesian techniques might be used for intermodel comparisons.

GOODNESS OF FIT AND VALIDATION BY FORECASTING

The question of whether a model is useful for decision making is usually related to an investigation of whether it describes the behavior of the real system in a manner that is compatible with the user's intentions. Cyert [56], Naylor [161, p. 159] and Howrey [119, p. 27] have listed a number of criteria that may be used to compare the output of a model with the output of the real system from a "goodness of fit" point of view. These criteria might involve a comparison of

1. the number of turning points,
2. the timing of turning points,
3. the direction of turning points,
4. the average amplitude of fluctuations for corresponding time segments,
5. the average values of variables,
6. the simultaneity of turning points for different variables,
7. the probability distribution, the mean and measures of variation about the mean of different variables.

As Naylor states [161, p. 159],these criteria have so far been used mainly in a qualitative manner to establish what has been termed the face validity of a model. However, he also supplies a list of quantitative statistical techniques that are available for such comparisons. Some of these might be included in a CSPS, examples being Theil's inequality coefficient [196, 197, 12, 171] or information inaccuracy test [198], Wold's Janus coefficient [85] or the von Neumann ratio [91].

MARKETING EXAMPLE

The Janus coefficient has been used by Kugler and Rosenkranz to compare real data with model data and model retrospective predictions for different marketing submodels describing sales of consumer products [132] An example is shown in Figure 6.14. Three period ahead forecasts of sales of a consumer product were generated (-) by a distributed-lag model and b triple exponential smoothing. The econometric model described sales as a function of a linear trend and the advertising expenditures. OLS estimation of a triangular lag distribution was employed. The adaptive exponential smoothing was carried out with some modifications suggested by Trigg and Leach [200] (*-*).

The Janus coefficient was employed to descriptively compare the two forecasts. The coefficient J with $0 \leq J \leq \infty$ is defined by

(6.80)
$$J = \left(\frac{\frac{1}{m} \sum_{t=n+1}^{n+m} (y_t - y_t^*)^2}{\frac{1}{n} \sum_{t=1}^{n} (y_t - y_t^*)^2} \right)^{1/2} \quad \text{, where}$$

the y_t are model values of the endogenous variable under investigation, y_t^* are the corresponding measurements of the real variable. The time interval $t = [1,n]$ has been used to fit the models, the interval $t = [n+1, m]$ is a prediction range for which measurements of the real variable are available. "The Janus coefficient is conceptually formed ex-post the obervation range and ex-ante the prediction range [85, p. 230]". It is calculated ex-post both ranges and expresses deviations between the model and the real system within the observation range by its denominator (D), deviations in the prediction range by its numerator. For very small J the observed and measured values nearly match and indicate that the predictions are somehow too good with respect to the models fit in the observation range, $J \approx 1$ indicates that a model is a good representation both for the observation and prediction range, whereas $J >> 1$ indicates very bad predictions. Using the identity

(6.81)
$$J^2 = J_m^2 + J_s^2 + J_c^2 \qquad \text{with}$$

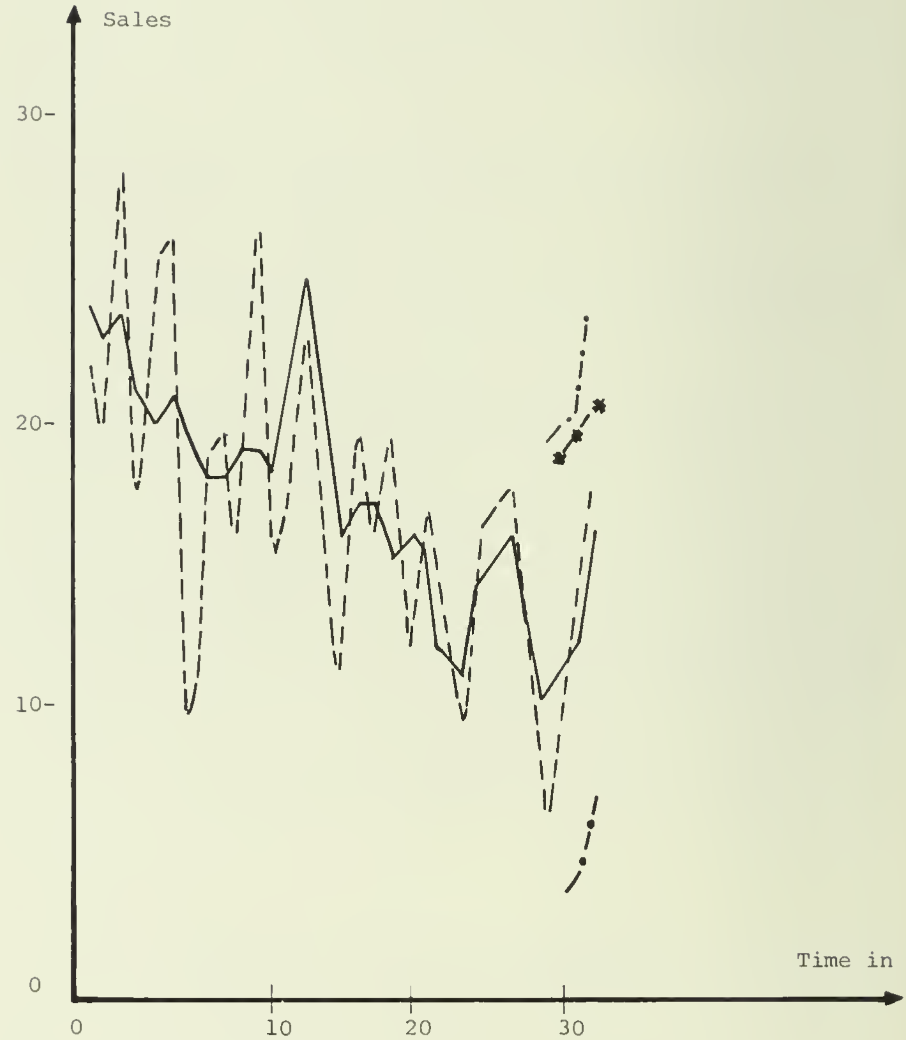
(6.82)
$$J_m^2 = \frac{(\bar{y} - \bar{y}^*)^2}{D^2}$$

(6.83)
$$J_s^2 = \frac{(s_y - s_y^*)^2}{D^2}$$

(6.84)
$$J_c^2 = \frac{2 s_y S_y^* (1 - r_{yy}^*)}{D^2} \quad ,$$

where s_y and s_y^* are empirical variances and r_{yy}^* the correlation coefficient between the y_t and y_t^* series respectively, one may decompose the coefficient. The coefficient J_m^2 represents a systematic prediction error, J_s^2 is proportional to errors in the variance of the forecast, J_c^2

Figure 6.14. Ex-post forecasting with an econometric (-) and an exponential smoothing model (*-*).



- - - ≙ Historical values

-|*- ≙ Exponential Smoothing Forecasts

– ≙ Econometric Model Values and Forecasts

-·-·- ≙ 90% Confidence Intervals of Forecasts

represents errors in covariances. Figure 6.15 gives the results of the analysis for the example.

Figure 6.15. Forecast error decomposition using Wold's Janus Coefficient

	JANUS Coefficient J^2	Predicition Error J_m^2	Variance Error J_s^2	Covariance Error J_c^2
Econometric Sales Forecasts	0.17	0.03	0.11	0.03
Expon. Smoothing Sales Forecasts	0.59	0.09	0.37	0.13

A qualitative comparison indicates the superiority of the explicative model, although the model values do not match the historic sales values too well. Similar results were obtained quite frequently. They suggest that the econometric models were able to pick up some of the causal relations between sales and advertising for the observation as well as for the prediction range (viz. also [6, 72, 162, 117]). Such results may be used to improve the firm's marketing decisions and demonstrate the value that formal statistical models may have in corporate modeling (viz. Kotler [128, 129, pp. 657-682]).

There are at least two reasons why formal statistical testing, as has been advocated above, has not found widespread application among corporate modelers so far. First, face validity and content are in many instances considered by model users to be sufficient conditions for model implementation and use. Second, many, if not the majority of hypotheses normally expressed in a corporate model, are not open to empirical testing, because data are missing and parameters are estimated only subjectively. One may perhaps predict that further research on model validation will bring about changes, either because the procedures currently available will be better known and new measures of validity will be developed, or because subjective probability viewpoints will be evaluated more formally.

MODEL EXPERIMENTATION AND ANALYSIS OF RESULTS [181]

When running a corporate model either in the validation step or after it is ready for implementation, the user is interested in the effect that values and variations about the values of his decision variables have on the values of the endogenous variables.[2]

Perhaps his intentions are best characterized by a remark of a manager who, after a model description, proposed: "Fine, now let us ask some "What if?" and "What to do to achieve?" questions here and there!"

EXPERIMENTATION IN PRACTICE

From the corporate modeling literature and one's own experience one may conclude that this questioning the model in practice is generally not systematized. The user usually has a good idea of which key variables he is interested in and by which decision variables he is able to influence those variables. Using the notation of chapter 2 eq. (2.10) the model may again be expressed by

$$\underline{f}_t\ (\underline{Y}_t, \underline{Y}_{t-1}, \underline{X}_t, \underline{\Theta}_t, \underline{U}_t) = \underline{O}\ ;\ t = [1,n]\ , \tag{6.85}$$

where, as before, $\underline{Y}_t$, $\underline{Y}_{t-1}$ denotes the endogenous and predetermined variables, $\underline{X}_t$ the exogenous, $\underline{\Theta}_t$ the decision variables of the model and $\underline{U}_t$ the stochastic disturbances that are possibly contained in it.
When experimenting with the model, the user in general is not interested in all endogenous and decision variables, but wants to explore the response of some key variables $\underline{Y}_t^*$ to absolute levels or changes in some of the decision variables denoted by $\underline{\Theta}_t^*$. The model may then more specifically be expressed by

$$\underline{f}_t\ (\underline{Y}_t^*, \underline{Y}_t^{**}, \underline{Y}_{t-1}^*, \underline{Y}_{t-1}^{**}, \underline{X}_t, \underline{\Theta}_t^{**}, \underline{\Theta}_t^*, \underline{U}_t) = \underline{O}\ , \tag{6.86}$$

where $\underline{Y}_t^{**}$ and $\underline{\Theta}_t^{**}$ represents the endogenous and decision variables he is not interested in during the experimentation. It should be noted that the variables $\underline{\Theta}_t^{**}$ are then kept at levels the user has chosen previously and that they may conceptually be treated as exogenous variables during the experimentation. The endogenous variables $\underline{Y}_t^{**}$ may be influenced by $\underline{\Theta}_t^*$ and

thus may change from experiment to experiment; but the user does not pay any attention to their values when he selects a certain experimentation strategy. The literature indicates that corporate model users mostly run their models in what should be called a trial and error sequential experimentation. It may be described as follows: in every experiment the user specifies the $\underline{\theta}_t^*$ he is interested in. Observations of the $\underline{Y}_t^*$ generated by the model in previous experiments and some a priori knowledge about the behavior of the real system than largely determine which experiments are carried out sequentially.

SOME PROBLEMS

Although this experimentation is practically very appealing, it obviously possesses two disadvantages. It does not guarantee that the model user obtains at all the information he is interested in. Furthermore, trial and error experimentation may be very ineffective and expensive compared with a planned experimentation. For the latter Cochran and Cox [49, pp. 10-14] have described a three stage analysis which should also be useful for experiments with large deterministic models (viz. Kleijnen [127], Rosenkranz, Bürgisser [181]):

1. The objectives of the experiment have to be clearly defined.
2. The experiment has to be described, i.e. controllable, uncontrollable factors and the response variable(s) have to be defined; the effects one is interested in have to be identified, hypoteses have to be formulated, the size and number of replications of the experiment and an experimental region have to be decided on.
3. A method of data analysis has to be chosen.

It seems that in practice it depends largely on the type of question the user wants his model to answer and whether the model is deterministic, i.e. $\underline{U}_t = \underline{O}$, or stochastic, how he should go about his planned experimentation. If he wants to know the values $\underline{\theta}_t^*$ that lead to optimal responses in the $\underline{Y}_t^*$, he is forced to formulate an objective function that in the simplest case could be expressed by $y_{t*} \to$ Max or $y_{t*} \to$ Min. This would indicate that he is interested only in the extremal values of one single endogenous variable at one specific time $t = t^*$ and values of $\underline{\theta}_t$, $t \leq t^*$ that result in that extremal value. Examples of such an application could be profits of the firm in a certain year or the sum of discounted income

margins y_t until the end of a time horizon $t = [1,n]$. In the case that he considers several endogenous variables or variables at different times, he encounters what in the literature has been called the multiple response problem (vix. Box et al. [25]).

A possible method of forming an objective function would be to incorporate subjective utility viewpoints in the formulation and to assign subjective weights to different variables and different times as has for instance been done for a long time in so called goal programming models (Charnes, Cooper, Ijiri [40, 41]). The example of a "What to do to achieve?" simulation given in chapter 4 illustrates such an application. Its objective function would be described by

$$(6.87) \qquad y_t^* = M_1 \ (YD_t^{+}* + YD_{t*}^{-}) + M_2 \ . \ YS_{2,t}* \rightarrow \text{Min}, \ t* = [1,n]$$

where M_1 and M_2 are subjectively supplied weighting factors with $M_1 >> M_2$. The user may now look for extreme values of y_t* in two ways: Either he performs a series of "What if?" experiments using trial and error thereby possibly achieving better and better decisions, or he applies available optimization techniques that may guarantee that he - without any experimentation - after an initial solution has been found reaches at least a relative optimum of his objective function automatically. Chapter 7 summarizes some of the available techniques.

Much the same arguments may be put forward when the user wants to experiment in such a way that the endogenous variables come as close as possible to predefined target values or stay below or above predefined sufficing values. Sufficing values would be dealt with in the case that only positive (i.e. YD_{t*}^{+}) or negative (i.e. YD_{t*}^{-}) deviations from the target values were considered. Indeed, as especially Rosenhead et al.[176 and Eilon [70] have argued, from a computational viewpoint the distinctio between a goal optimizing, a goal sufficing and a robustness approach are rather arbitrary and in principle the problem of obtaining robust or sufficing solutions to a model may be understood as a special subproblem of the general optimization problem. Again the user may produce model solutions by a series of "What if?" experiments or automatically by the application of optimization methods as are currently available.

In the latter case the question asked would be one not involving any decision variables directly, since the special optimization method applie would supply values of the decision variables automatically. In principle

they could be treated like endogenous variables after their initial values have been decided upon.

In both cases, the optimization experiment and the "What if?" experiment, the user can handle his experiment in different ways. Although an unsystematic application of the trial and error method using "What if?" investigations is only a method of "last resort", it may be the only practically feasible way of testing the models response to changes in the decision variables. This may especially be the case, whenever the model contains a great number of variables, a great number of equations or inequalities possibly comprising complicated non-linearities, non-conjunctive terms and stochastic disturbances. It is especially the problem of high dimensionality or size that has made this method so appealing to corporate model users. However, other experimental approaches are at least worth a short investigation.

DETERMINISTIC RESPONSE SURFACES AND LOCAL APPROXIMATIONS [210, 181]

Provided that the model eq. (6.86) is completely deterministic, as is the case with the predominant number of corporate models that are currently known, two experiments with identical values of $\underline{\theta}_t^*$ would obviously give identical values of the endogenous variables $\underline{Y}_t^*$. Therefore different values of $\underline{\theta}_t^*$ are used to obtain information about the endogenous variables $\underline{Y}_t^*$. In the simplest case of a model that only consists of linear algebraic equations, the $\underline{Y}_t^*$ are a linear function of the $\underline{\theta}_t^*$. As a consequence only (M+1) experiments have to be performed to uniquely determine a response surface for all the $\underline{Y}_t^*$, assuming linear independence among the $\underline{\theta}_t^*$. The constant M denotes the number of decision variables, where the same decision variables for various times are counted as different variables. The number of necessary experiments is (M + 1), because one experiment has to be used to determine the constant term in the equation representing the $\underline{Y}_t^*$ as a function of the $\underline{\theta}_t^*$. The values and "distances" between the $\underline{\theta}_t^*$ are of no importance, because the response surface is a linear hyperplane in the whole region of admissible $\underline{\theta}_t^*$. Figure 4.7 in chapter 4 represents an example of such a response surface: Total variable profits YT_t are parametrically represented as a function of sales prices θP_{1t} and θP_{2t}. In many corporate modeling applications, especially in the financial area, it has been overlooked that model segments are often linear and that a small number of experiments allows one

to calculate a linear deterministic model of the original linear deterministic model. Most of the questions related to "What if?" partially also to "What to do to achieve?" type investigations may then be carried out using a very simple model of the model without any further experimentation

Linear Approximation

Much the same arguments hold whenever the response of a nonlinear deterministic model is investigated. If one considers a nonlinear model in which one response variable y_t^* is explicitly represented by

$$(6.88) \qquad y_t^* = g\,(y_{t-1}^*,\ \underline{Y}_t^{**},\ \underline{Y}_{t-1}^{**},\ \underline{X}_t,\ \underline{\theta}_t^*,\ \underline{\theta}_t^{**}),$$

then a local Taylor expansion at $\bar{\underline{\theta}}_t^*$ up to linear terms gives

$$(6.89) \qquad y_t^* \simeq \bar{Y}_t^* + \sum_{i,t'\leq t} a_{it'} \cdot (\theta_{it'}^* - \bar{\theta}_{it'}^*) .$$

The coefficients $a_{it'}$ correspond to the derivatives

$$(6.90) \qquad a_{it'} = \left(\frac{\partial y_t^*}{\partial \theta_{it'}^*}\right)_{\bar{\underline{\theta}}_{t'}^*}$$

and the constant $\bar{y}_t^*$ is expressed by

$$(6.91) \qquad \bar{y}_t^* = g\,(y_{t-1}^*,\ \underline{Y}_t^{**},\ \underline{Y}_{t-1}^{**},\ \underline{X}_t,\ \bar{\underline{\theta}}_t^*,\ \underline{\theta}_t^{**}) .$$

Eq. (6.91) is a tangent plane approximation to the surface expressed by eq. (6.88) and again (M+1) experiments are sufficient to calculate all coeffieients in eq. (6.89). Since the model is non-linear, the tangent plane can only locally approximate the true response surface. Therefore M trial points should be taken as closely to $\bar{\underline{\theta}}_t^*$ as possible for a local investigation of the surface.

If one, by contrast, is interested in the average linear behavior of the response surface in a region of admissible $\underline{\theta}_t^*$, one may choose trial experiments by random according to one of the experimental design schemes indicated below and estimate the approximating surface applying the least squares principle. This would then correspond to the introduction of stochastic disturbances in the model of the model due to a functional misspecification. In any case the number of experiments will be larger than (M+1).

Quadratic Approximation

While a linear approximation of the response surface may often be sufficient and easy to calculate in regions of the surface that do not contain extrema or singularities such as saddle-points or parabolic points, one may be interested in a more accurate approximation to the true surface especially near an extremum. In this case one would either locally or as an average fit a second degree (or higher order) surface by numerically evaluating the coefficients of the Taylor expansion up to quadratic terms given by

$$(6.92)\qquad y_t^* \approx \bar{y}_t^* + \sum_{i,t' \leq t} a_{it'} \cdot (\Theta_{it'}^* - \bar{\Theta}_{it'}^*) + \frac{1}{2} \sum_{i,j,t' \leq t} b_{ijt'} (\Theta_{it'}^* - \bar{\Theta}_{it'}^*) \cdot (\Theta_{jt'}^* - \bar{\Theta}_{jt'}^*) ,$$

$$(6.93)\qquad b_{ijt'} = \left(\frac{\partial^2 y_t^*}{\partial \Theta_{it'}^* \, \partial \Theta_{jt'}^*} \right)_{\underline{\bar{\Theta}}_{t'}^*} .$$

For a local fit $\frac{1}{2}(M^2 + 3M+2)$ experiments close to $\underline{\bar{\Theta}}_t^*$ would be sufficient to calculate all parameters $\bar{y}_t^*$, $a_{it'}$, $b_{ijt'}$. Analytic geometry supplies a number of simple transformation formulas that permit a more detailed investigation of the surface eq. (6.92). A number of two-dimensional plots can then easily reveal the general nature of the surface to the user.

Discontinuities

In the discussion it has been assumed so far that the response y_t^* may be represented as a smoothly varying function of the decision variables $\underline{\Theta}_t^*$, i.e. that the response surface or even its derivatives are continuous. In many practical situations this will not be the case. A very simple example may illustrate this point: Consider a firm that is able to produce two products in quantities Θ_{1t}^* and Θ_{2t}^*. It possesses two plants that are able to supply these quantities, but due to differing variable production costs resulting profits y_t^* will also be different. Assume that the firm decides to produce in the plant which for a certain combination of Θ_{1t}^* and Θ_{2t}^* gives higher profits. With $g_1(\underline{\Theta}_t^*)$ and $g_2(\underline{\Theta}_t^*)$ denoting the profit functions in the two cases,

$$(6.94) \qquad y_t^* = \max\left(g_1(\underline{\Theta}_t^*),\ g_2(\underline{\Theta}_t^*)\right)$$

$$\underline{\Theta}_t^* \geq \underline{0}$$

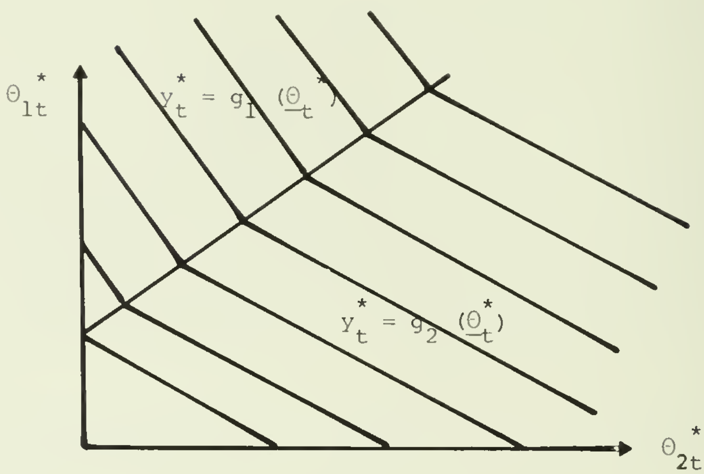
describes this policy. With

$$(6.95) \qquad g_1(\underline{\Theta}_t^*) = a_{01} + a_{1i}\Theta_{1t}^* + a_{21}\Theta_{2t}^* \quad \text{and}$$

$$g_2(\underline{\Theta}_t^*) = a_{02} + a_{1t}\Theta_{1t}^* + a_{22}\Theta_{2t}^*$$

Figure 6.16 could be a parametric representation of y_t^* .

Figure 6.16. Response surface for qualitative policies



The example shown suggests that it may take a great number of experiments to uncover the behavior of the response surface for large models containing non-linearities and non-conjunctive relations. A series of "What if?" experiments that relate directly to the decision alternatives in question may often be the only experimentation strategy which is feasible from a computational viewpoint. However, it depends a lot on how

"close" to the response discontinuities in the model variables occur. In some instances the values of such variables are fed into first and higher order difference equations with the effect that they "smooth out" in the response under investigation.

STOCHASTIC RESPONSE SURFACES AND PLANNED EXPERIMENTS

While any two experiments with identical values of the decision variables $\underline{\Theta}_t^*$ result in the same response y_t^* with deterministic models, they will in general differ with stochastic models. In fact, this will always be the case if the parameters of some model equations have been estimated by standard econometric techniques. Either the parameters in such an equation are treated as fixed quantities and stochastic disturbances $\underline{U}_t$ describe deviations from the deterministic part of the equations, or the parameters are looked upon as random variables that have a multivariate probability distribution.

A number of authors (viz. Holt [115], Mihram [151]) have proposed a deterministic experimentation with stochastic models. This can be achieved by just using expected parameter values in an experiment and neglecting all stochastic disturbances. It is well known that such experiments lead to the expected values of the response with models that are linear in the model variables. Thus the response surface describing an expected response variable $\varepsilon\{y_t^*\}$ as a function of the decision variables $\underline{\Theta}_t^*$ may be explored with the same technique that has been proposed for linear deterministic models. It is known equally well that with stochastic linear models the distribution properities of y_t^* may be derived in principle by analytical techniques, once the properties of the stochastic disturbances are known. Therefore an experimentation with a stochastic model does not deliver more information about the response than is available from an analytical solution [viz. 118]. But one will still experiment with the stochastic model in many instances, because in practice an analytical solution, especially of a large model, may be harder to obtain than results from a series of experiments even from the viewpoint of computational economy. This argument has been stressed especially by Naylor [161, p. 318]. This is even more true whenever one deals with models that are non-linear in the model variables. As notably Howrey and Kelejian [118] have shown, one can expect a systematic deviation between the response of the deterministic and stochastic models. In practice this would mean that experiments

with the deterministic model deliver inaccurate or wrong information about the response surface of the stochastic model. Especially if questions of risk and uncertainty are dealt with in an investigation, as is the case with financial submodels describing investment projects with uncertain cash flow, this may lead to serious misjudgements by the model user. Therefore experimentation with the stochastic model will sometimes be preferred.

When experimenting with a stochastic model, one is faced to a large extent with the same problems that industrial statisticians and natural scientists encounter in experiments with real world systems. In both cases one takes stochastic disturbances into consideration which may result from errors in measurements or the functional form of a model. The objective of the experimentation is to obtain a deeper understanding of the relation between the response and the factors or decision variables that are thought to influence the response. More specifically one might be interested in whether a decision variable has a significant influence on the response, how strong its influence is, whether its influence is significantly different or stronger than that of other variables or how a group of decision variables has to be adjusted to obtain an extreme response.

Industrial statisticians beginning with Fisher [78], more recently notably by Box and coworkers [16-20, 25, 26], have developed a great number of so called experimental designs that may be used with real world systems and their corresponding models to aid in such investigations. These experimental designs

"... have been created to provide not only economy in the number of experimental trials but such additional qualities as minimum variance estimates, measures of the adequacy of the models, desireable confounding patterns, and ease of computation (Naylor [161, p. 165])".

A very extensive literature on experimental design techniques exists today and the reader is referred to the books by Cochran and Cox [49], Cox [54], Davies [57], Linder [139] or Chakravarti, Laha and Roy [36]. Especially in the marketing area a number of real world application are known [10, 113, 116] and the books by Banks [9], Cox, Enis [55] and Kotler [129] deal with the subject. Possible applications to computer simulation models have been described by Hunter, Naylor [120], Bonini [14], Kleijnen [127] and Williams, Weeks [213]. Experimental design techniques do not only deal with systematic ways of experimentation, but also investigate different techniques of statistically evaluating the output data generated

by an experiment. In most cases either the analysis of variance or multiple regression analysis were used. The books by Scheffé [183] and Draper, Smith [67, 187] discuss their application very extensively.

Experimental designs may be combined with optimization algorithms [112] for the optimization of stochastic models. Box and Wilson [16] gave a first unconstrained example. Extension may be found in [7, 104, 141, 189, 108. 127, 153]. So called robust designs may be of interest in experiments incorporating large stochastic disturbances and have been described by Box and Draper [26].

Some practical examples for a planned experimentation with corporate models will be given in chapter 9.

Planned Experiments And Data Analysis

In a planned simulation experiment with a stochastic model as expressed by eq. (6.85) again an approximation or 'metamodel' (viz. Kleijnen [125]) to the true model is chosen. Its parameters are estimated from experiments with the true model. Let

$$y = g\,(\underline{\Theta}^{*}\,,\ \underline{u}) \tag{6.96}$$

describe the metamodel; y is the response variable, $\underline{\Theta}^{*}$ denotes all quantitative or qualitative decision variables or factors which may be varied in a simulation experiment, $\underline{u}$ denotes stochastic variables which may represent stochastic effects due to $\underline{U}_t \neq 0$ in eq. (6.85). They may, however, also arise from approximation or equation errors, even for a purely deterministic model.

Depending on the chosen approximation the factors $\underline{\Theta}^{*}$ are varied according to an experimental scheme within an experimental region. The corresponding values of y are obtained from the true model. Both, the measurements of the response y and the values $\underline{\Theta}^{*}$ of the factors are employed in the estimation of main-effects, interaction-effects or parameters of the approximate model eq. (6.96). In most cases either variance or regression analysis is employed for such computations (viz. Scheffé [183], Draper, Smith [67, 187]). Whereas the first techniques may be used with qualitative and quantitative variables, regression analysis requires measurement of quantitative factors.

The experimental schemes are frequently choses in such a way that all computations are easy to perform, avoid the confounding of effects,

possess a high accuracy and permit statistical specification and verification tests. Such tests tell the user whether his a priori specified metamodel is a good approximation to the true model.

In the simplest case of one response variable and three factors which are denoted by F_1, F_2, and F_3 the metamodel for an application of variance analysis is described by

$$(6.97) \qquad y_{ijkg} = a_o + a_i^{F_1} + a_j^{F_2} + a_k^{F_3} + a_{ij}^{F_1F_2} + a_{ik}^{F_1F_3} + a_{jk}^{F_2F_3} + a_{ijk}^{F_1F_2F_3} + u_{ijkg} ,$$

where g denotes the number of the experiment; i,j and k the levles of the factors F_1, F_2, and F_3. The quantity $a_i^{F_1}$ represents the so called main-effect of F_1 on level i, $a_{ik}^{F_1F_2}$ e.g. the interaction effect of F_1 and F_2 on levels i and k. Finally, $a_{ijk}^{F_1F_2F_3}$ describes a three factor interaction effect on levels i, j and k. Except for the stochastic disturbances u_{ijkg} measurement values of y_{ijkg} are described by the arithmetic mean a_o and the effects. For the u_{ijkg} it is usually assumed that they have an independent normal distribution with zero mean and constant variance. This assumption forms the basis for parametric specification testing both with variance and regression analysis. Note that eq. (6.97) does not allow for higher order effects in one decision variable or factor.

If all factors are only varied on two levels one may show that all effects in eq. (6.97) may be estimated from the equivalent regression model

$$(6.98) \qquad y_g = a_o + \sum_{i=1}^{3} a_1^{F_i} \Theta_{ig}^* + \sum_{i=1}^{3} \sum_{j=(i+1)}^{3} a_{11}^{F_iF_j} \cdot \Theta_{ig}^* \Theta_{jg}^* + a_{111}^{F_1F_2F_3} \cdot \Theta_{ig}^* \Theta_{2g}^* \cdot \Theta_{3g}^* + u_g \quad .$$

Considering eq. (6.98) it should be noted that, first, effects in eq. (6.97) cancel, if they are averaged over one of the indices i,j,k; second, that Θ_1^*, Θ_2^*, Θ_3^* in eq. (6.98) only take values of $\pm$ 1 (low and high factor level). It follows for example, that $a_1^{F_1} = -a_2^{F_2}$ or $a_{11}^{F_1F_2} = a_{22}^{F_1F_2} = -a_{12}^{F_1F_2} = -a_{21}^{F_1F_2}$. For qualitative variables the notation of factor levels only has a nmemonic meaning (e.g. $\Theta_{1g}^* = -1 \hat{=} F_1$ (low level) ; $\Theta_{1g}^* = +1 \hat{=} F_1$ (high level)). Levels of quantitative factors

may always be transformed into ± 1 by a simple linear transformation. Such a transformation reduces rounding errors and for special design schemes results in orthogonal matrices of factor measurements. Note also that the regression model eq. (6.98) is more general than the variance analysis model eq. (6.97), since it allows for higher order effects in quantitative variables, such as $a_{11}^{F_1} \cdot \Theta_{1g}^{*2}$ or $a_{111}^{F_1 F_2} \Theta_{1g}^{*} \cdot \Theta_{2g}^{*2}$.

The number of simulation experiments with the true model must at least be equal to the number of effects assumed in the approximating model. Additional experiments are required in order to obtain an estimate of the variance of u_{ijkg} or u_g as is needed for econometric specification and verification testing. Note, however, that in so called screening experiments the number of experiments may be considerably smaller than the number of effects. Such experiments may be used to determine whether a certain factor contributes considerably to an explanation of the variance in y or not (viz. Kleijnen and ref. [124]).

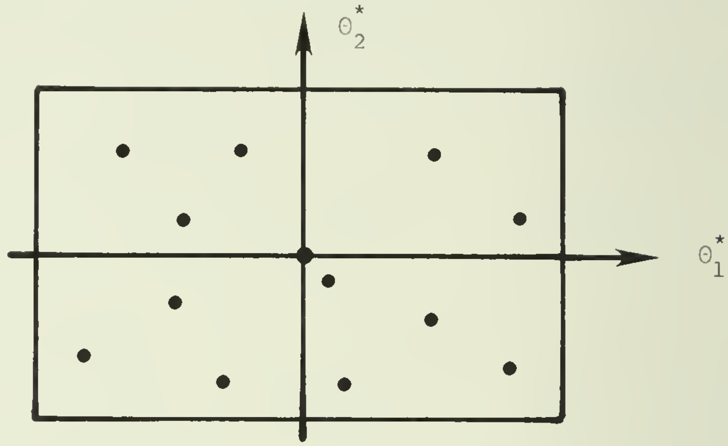
For experiments with deterministic response surfaces or econometric models, one mainly chooses metamodels which are linear in the parameters or effects. This simplification is in most cases justified, because the approximate model may be understood as a Taylor expansion of the true non-linear model in the experimental region. There are also a great number of transformation formulas available which allow a linearization of model variables (viz. e.g. Box, Cox [21]).

Random Balance Designs

They have been described by Satterthwaite [182] and Budne [34] and may be used with qualitative and quantitative variables. Their values are randomly and independently chosen in an experimental region as is shown in Figure 6.17 for a two factor example. In most cases experiments are generated from a uniform distribution random generator.

Random balance experiments correspond to unplanned experiments and possess a number of undesirable statistical properties. Box [19] notes the small efficiency of estimates obtained from random balance designs. The matrix of factor values is not orthogonal. As a consequence the variance-covariance matrix of the estimates is not a diagonal matrix. In comparison to the design schemes described below, the estimated parameters possess a large variance. Futhermore, confoundings of effects are not under the control of the experimentor.

Figure 6.17. Experiments random balance design

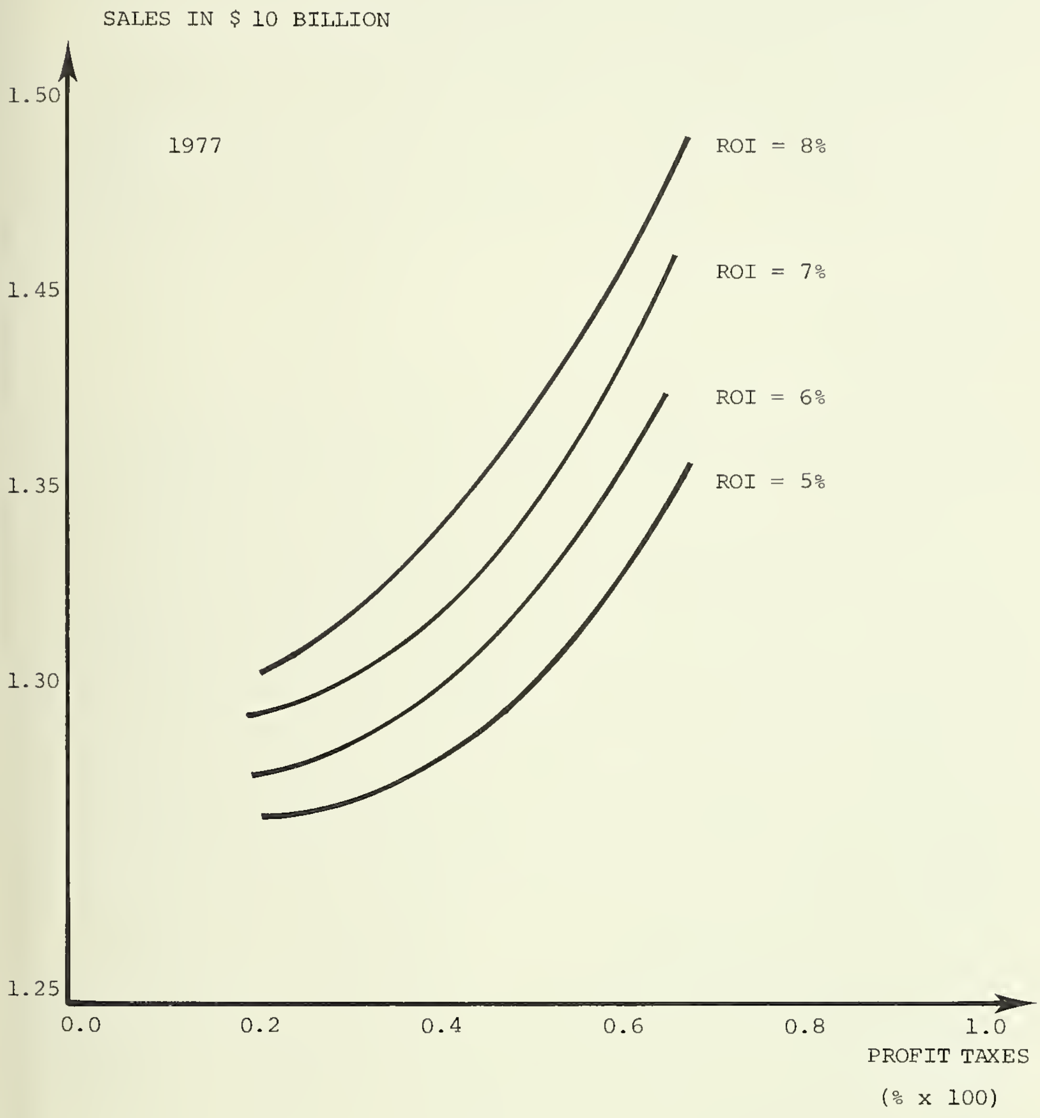


The advantages connected with random balance experimentation make them nevertheless sometimes look attractive: they are extremely easy to realize on a computer. The number of factors or variables in an experiment may be much larger than the number of measurements in screening experimentation. Important factors may be isolated in a stepwise regression analysis. The designs do not have to be adapted to a certain type of metamodel eq. (6.96) like the designs described below. Finally, quantitative factors are not only varied on a few factor levels. This may be an advantage if an average property of a response surface is of interest.

Figure 6.18 shows an output from a random balance experiment. It was generated by experiments with a CIBA-GEIGY financial corporate model that will be described more explicitely in chapter 9. The given figures have been distorted. The return on investment of the corporation is shown parametrically as a function of total sales and an average profit tax rate for a given planning year. A quadratic approximation in the region 5% $\leq$ ROI $\leq$ 8% and 20% $\leq$ P. Taxes $\leq$ 70% was used to estimate the response function. Ten Monte-Carlo experiments were sufficient for the estimation of in total six coefficients. A more extensive experimentation with the model revealed that - except for a narrow region of small ROI and small profit taxes - the estimated response surface deviated less than one percent from the true surface.

Return on investment (ROI) of the corporation is indeed a very complex function of a great number of other variables on the company, divisional and sub-divisional level. It is important to note that it contains

Figure 6.18. Example for quadratic approximation to a response surface



lagged endogenous variables, like sales in previous years. Also these variables could have been used in a graphical representation of the response surface. The model was deterministic and the stochastic disturbance u_g is introduced by the quadratic approximation.

Full and Fractional Factorial Experimentation

The disadvantages noted for random balance designs are largely avoided by factorial experimental designs (viz. Box and Hunter [20]). They are mainly used if higher order effects in the variables or factors do not have to be considered. The variables are mostly varied on two, sometimes three levels only.

Full Factorials

In a full factorial experiment one defines the levels of the variables $\underline{\Theta}^*$ under study and then carries out one or several experiments with each of the possible combinations of variable values. With a deterministic model, one experiment would be sufficient for every combination. With a stochastic model experiments have to be replicated in order to calculate an estimate for the expected response $\varepsilon\{y\}$ with sufficient accuracy. In the symmetric case in which every variable possesses m levels, obviously m^k level combinations are possible, where k is the number of policies or decision variables, $\underline{\Theta}^*$, under investigation. It follows that $n \cdot m^k$ experiments have to be performed, provided that every combination is simulated n times. It becomes immediately clear that factorial experimentation in practice is feasible only for a relatively small number of variables and levels. Consider for example experimentation with a model in which there are five decision variables Θ_1^*, Θ_2^*, ... Θ_5^* each having three levels. In total 243 combinations would have to be investigated. If one experiment with the model tool 0.1 min (which for a large corporate model even on a modern computer may easily happen) and ten replicates were necessary to estimate the mean response, it would take approximately four hours of computer time to carry out all experiments.

However, compared to other designs, a full factorial design possesses a number of desireable properties that make it attractive in a number of situations:

1. Using a factorial design "... the effect of changing any one variable can be assessed independently of the others [57, p.247]" If one defines as an ℓ - th order interaction between variables

$\underline{\Theta}^*$ an effect on y^* in which the effect of changing one of the variables depends on the levels of the remaining (ℓ-1) variables then a factorial design supplies information not only about zero order interactions or so called main effects, but also about all the other possible interactions. In a design that changes one variable at a time, for instance, this would not be possible.

2. The design is efficient in the sense that "... a maximum amount of information is obtained with a minimum number of experiments [57, p. 270]". If only main effects have to be considered a factorial design gives maximum efficiency (i.e. smallest variance) in the estimates.

3. The "... effects of a factor is estimated at several levels of the other factors, and the conclusions hold over a wide range of conditions [57, p.253]". This helps especially to recognize key variables that have the greatest effect on the response. Furthermore when looking for an optimal adjustment of the decision variables the results obtained from factorial experiments are very likely to indicate directions of improvement.

A simple example might illustrate an application of full factorial experimentation: Consider a corporate model for which one wants to investigate the dependence of net present worth of profits in the interval $t = [1,n]$ y_t^* on inventory (Θ_{1t}^*), liquidity (Θ_{2t}^*) and advertisement (Θ_{3t}^*) policy. Assume that there are two levels, denoted by ((+) $\hat{=}$ high) and ((-) $\hat{=}$ low, to every policy and that these policies stay constant over time for the experiment. Since one deals with a 2^3 factorial experiment, the possible level combinations may be visualized by Figure 6.20.

Due to possible stochastic disturbances of the model, experiments would be replicated, according to a principle of symmetry, perhaps an equal number of times for every combination. For every experiment one would record the response y_t^* and calculate means for every combination. These values then allow the estimation of the three main effects of Θ_{1t}^*, Θ_{2t}^* and Θ_{3t}^*, the three effects of first order interaction Θ_{1t}^* Θ_{2t}^*, Θ_{1t}^* Θ_{3t}^*, and Θ_{2t}^* Θ_{3t}^*, the second order interaction effect Θ_{1t}^* Θ_{2t}^* Θ_{3t}^* and the residual variance. Using analysis of variance or regression analysis and appropriate values of the F- and t- statistics one is then able to test hypotheses related to these effects under the usual assumptions.

Figure 6.19. 2^3 full-factorial experiment

Θ^*_{1t} ADVERTISING	Θ^*_{2t} INVENTORIES	Θ^*_{3t} LIQUIDITY
+	+	+
-	+	+
+	-	+
-	-	+
+	-	-
-	+	-
+	+	-
-	-	-

Fractional Factorials

It has been noted before that a full factorial design may not be feasible in practice, because of economical reasons. It is especially for these problems that a number of other designs have been developed that only use subsets of the combinations needed for a full factorial design. They have in common that they require some a priori knowledge about the variable interactions from the experimenters side. If such knowledge is not available he takes the risk of obtaining biased estimates, because effects may be present that are assumed to be negligible for a special design scheme. In the case that all first and higher order interactions are negligible and the number of levels for every decision variable or policy is equal, Latin square designs may be used. More general designs are fractional factorial designs. Figure 6.20 shows a design scheme with four variables or policies, the fourth one being a sales price policy [57, p.448].

Instead of 2^4 combinations needed for a full factorial design, only 2^3 combinations are investigated. The trade off connected with such an experiment would be that the following interactions could not be estimated independently from the experiments: $\Theta^*_{1t} \cdot \Theta^*_{2t} \cdot \Theta^*_{3t} - \Theta^*_{4t}$; $\Theta^*_{1t}\, \Theta^*_{2t}\, \Theta^*_{4t} - \Theta^*_{3t}$; $\Theta^*_{1t}\, \Theta^*_{3t}\, \Theta^*_{4t} - \Theta^*_{2t}$; $\Theta^*_{1t}\, \Theta^*_{2t} - \Theta^*_{3t}\, \Theta^*_{4t}$; $\Theta^*_{1t}\, \Theta^*_{3t} - \Theta^*_{2t}\, \Theta^*_{4t}$;

$\Theta_2^* \Theta_{3t}^* - \Theta_{1t}^* \cdot \Theta_{4t}^*$. Especially the main effects could only be estimated if all second order interactions are negligible. It is interesting to note that with eight combinations even the main effects of a two level - seven variable design may be estimated if higher order interactions may be neglected. Such an experiment would involve 2^3 instead of $2^7 = 128$ combinations needed for the full factorial experiment.

While fractional or full factorial designs together with analysis of variance are mainly used to investigate the effects of qualitative policies on the response variable, this experimentation may easily be extended to also deal with the investigation of the effects of quantitative policies. One can imagine that the "+" and "-" sign used in Figure 6.19 corresponds to the numeric values of the variables shown in Figure 6.21.

Measurements of the response y_t may now be used with the above values of the decision variables to estimate the coefficients a_i, i = [0,7] of linear models, such as

$$y_t = a_o + a_1 \cdot \Theta_{1t}^* + a_2 \cdot \Theta_{2t}^* + a_3 \cdot \Theta_{3t}^* + u_t \tag{6.99}$$

or

$$y_t = a_o \cdot \Theta_{1t}^* + a_1 \cdot \Theta_{2t}^* + a_2 \cdot \Theta_{3t}^* + a_4 \cdot \Theta_{1t}^* \cdot \Theta_{2t}^* + a_5 \cdot \Theta_{2t}^* \cdot \Theta_{3t}^* + a_6 \cdot \Theta_{1t}^* \cdot \Theta_{3t}^* + a_7 \cdot \Theta_{1t}^* \cdot \Theta_{2t}^* \cdot \Theta_{3t}^* + u_t \tag{6.100}$$

by standard multiple regression techniques (viz. Cochran and Cox [49, pp. 335-339]). In both equations u_t would again denote a stochastic disturbance. To obtain estimates of the variance of u_t needed to carry out significance tests or to construct confidence limits, more than the eight experiments shown above would be required. However, with eq. (6.99) there are four degress of freedom left to test whether the linear model is a sufficient approximation to the response surface (higher order interactions).

If effects porportional to higher powers of the factors or decision variables, such as Θ_{1t}^{*2}, Θ_{2t}^{*2} and Θ_{3t}^{*2}, have also to be considered, one is forced to vary the decision variables on more than two levels. One could still use full or fractional factorial designs for such investigations, but this would have mainly two disadvantages. First, the number of

Figure 6.20. Fractional factorial design for four policies

Θ^*_{1t} ADVERTISING	Θ^*_{2t} INVENTORIES	Θ^*_{3t} LIQUIDITY	Θ^*_{4t} PRICE
-	-	-	-
+	-	-	+
-	+	-	+
+	+	-	-
-	-	+	+
+	-	+	-
-	+	+	-
+	+	+	+

Figure 6.21. Quantitative factors corresponding to Figure 6.19

Θ^*_{1t} ADVERTISING [$]	Θ^*_{2t} INVENTORIES [Units]	Θ^*_{3t} LIQUIDITY [Coefficient]
1000	50	2
400	50	2
1000	40	2
400	40	2
1000	40	1
400	50	1
1000	50	1
400	40	1

experiments would increase very quickly with the number of levels. For the given example one would have to use a 3^3 factorial design instead of the 2^3 design to estimate a model allowing quadratic effects. Second, as Box and Wilson [16] have shown, the estimates obtained for the coefficients of the squared terms from a 3^k factorial experiment would have a relatively low precision.

Rotatable Designs

Because of these disadvantages especially Box and coworkers [17, 18, 35, 66, 49, 57] have developed a number of so called rotatable experimental designs that may be used for the investigation of the effects of quantitative policies. These designs mostly require less experiments than the corresponding factorial designs. They also allow the estimation of regression coefficients of polynomial models that give an approximately equal standard error of the estimated response $\hat{y}_t$ within a circular or spherical region of the decision variables. Experimental points are chosen on the surface of the circle, sphere or hypersphere and in the centre. The latter is replicated a specific number of times more often than the points on the surface to ensure a more or less constant variance of $\hat{y}_t$ within the region of the $\underline{\Theta}_t^*$. For the example of Figure 6.21 one would calculate the values of the response for the eight points of the 2^3 factorial design or a fraction of it. These experiments would then by augmented by another six 'star' experiments as are shown in Figure 6.22 and an additional six experiments at the (centre) coordinates

Figure 6.22. Star points for three variable second order rotatable design

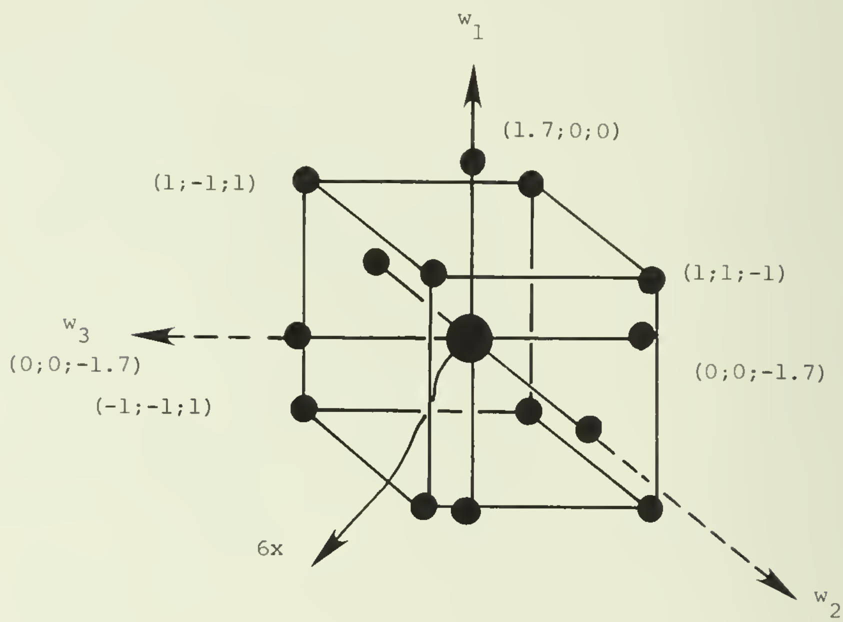
Θ_{1t}^*	Θ_{2t}^*	Θ_{3t}^*
195.4	45	1.5
1204.6	45	1.5
700	36.6	1.5
700	53.4	1.5
700	45	0.66
700	45	2.34

$\Theta^*_{1t} = 600$, $\Theta^*_{2t} = 45$, $\Theta^*_{3t} = 1.5$. Using the linear transformations

$$w_{1t} = \frac{\Theta^*_{1t}}{300} - \frac{7}{3} \; ; \; w_{2t} = \frac{\Theta^*_{2t}}{5} - 9 \; ; \; w_{3t} = 2\,\Theta^*_{3t} - 3,$$

one can easily show that all experimental points are either situated in the centre or on the surface of a sphere with radius r = 1.682. Figure 6.23 is an illustration of the design in the space of the transformed decision variables (viz. [17, p. 34]).

Figure 6.23. Three variable second order rotatable design



In every experiment except the centre one were carried out only once, one would have to perform a total of twenty experiments to fit the response surface

$$y_t = a_o + a_1\Theta^*_{1t} + a_2\Theta^*_{2t} + a_3\Theta^*_{3t} + a_4\Theta^*_{1t}\Theta^*_{2t} + \tag{6.101}$$

$$+ \quad a_5\Theta^*_{1t}\Theta^*_{3t} + a_6\Theta^*_{2t}\Theta^*_{3t} + a_7\Theta^{2*}_{1t} + a_8\Theta^{2*}_{2t} + a_9\Theta^{2*}_{3t} + u_t \,.$$

Since these experiments are carried out sequentially on a computer, one may start the experiments with a full or fractional factorial screen-

ing design, analyze the results using analysis of variance or multiple regression to judge whether a linear approximation is adequate and only continue the experimentation if the result is negative.

Conclusion and Computer Realization

Unfortunately, insufficient attention has been given in the literature on corporate simulation models to the questions of validation, experimental design and analysis of data generated by simulation experiments. Practitioners appear to have, for the most part, completely ignored these issues in going about the business of implementing actual corporate simulation models. Until recently, computer software was not available to facilitate the solution of these rather serious methodological problems.

Recently, computer software for planned experimentation has become available ([Peng, 168]). If required, one may attach such software to a CSPS. Language intercommunications facilities may be required for such a solution.

One may summarize the above arguments, indications and examples as follows: The experimentation with a corporate model may often very closely resemble the experimentation one would carry out with a real system. Although a "trial and error" or random experimentation is sometimes the only kind of investigation with the model that is feasible from the point of view of computational economy, especially if the model contains a great number of non-conjunctive relations, non-linearities and stochastic disturbances, in most cases some thought should be given to planned experimentation with the model. Planned experimentation provides in many cases a relatively high computational efficiency and a sounder basis for inductive conclusions regarding model adequacy and qualitative as well as quantitative effects of changes in the key decision variables. Such an experimentation will in most cases be preceeded by a three step investigation consisting of the formulation of the objectives of the experimentation,

a description of the experiment and a specification of the intended data analysis and representation.

The experimental designs described in the previous chapters have been realized in an integrated fashion for the CIBA-GEIGY CSPS COMOS. The software relies on statistical macros which were developed for the specification and estimation of econometric models. Both variance analysis and regression models may be estimated. Integrated plot macros permit a representation of the response surfaces. Additional macros were developed for the generation of specific experimental designs. Rosenkranz and Bürgisser [181] give more explicit description of the design subsystem.

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FOOTNOTES TO CHAPTER 6

1. Attention has to be given to the fact that measurements and degrees of freedom are lost by the differencing operations.

2. It should be noted that the model user may also test the response of the endogenous variables with respect to changes in the exogenous variables or model parameters by a simulation. While they would be uncontrollable factors in an experiment with the real system, they can be treated like controllable factors in a simulation experiment. If they are changed on a planned basis in such an experiment, they will in the sequel be treated like decision variables, although in reality they may not be.

The Role of Optimization

INTRODUCTION

The system of equations

(7.1) $\underline{f}_t\ (\underline{Y}_t, \underline{Y}_{t-1}, \underline{X}_t, \underline{\Theta}_t, \underline{U}_t) = \underline{O}\ ,\ t = [1,n]$

or in linear form

(7.2) $A\ .\ \underline{X}_t + B\ .\ \underline{Y}_t + B_1\ .\ \underline{Y}_{t-1} + C\ .\ \underline{\Theta}_t + \underline{D} = \underline{U}_t,\ t = [1,n]$

describes the firm's development in time and at different locations. As defined previously, the (ℓ x 1) vector $\underline{X}_t$ represents the exogenous variables of the model, $\underline{Y}_t$ and $\underline{Y}_{t-1}$ (k x 1) vectors of endogenous and predetermined variables, Θ_t a (h x 1) vector of decision, policy or instrumental variables, $\underline{D}$ and $\underline{U}_t$ (m x 1) vectors of constants and stochastic error terms; A, B, B_1 and C are coefficients matrices of dimensions (m x l) (m x k) and (m x h), respectively.

It is difficult to make any general statement about solutions to the general model described by eq. (7.1). We have previously indicated in chapter 2 that there are several techniques at hand with which the system may be solved for the $\underline{Y}_t$ or the Θ_t provided that such solutions exist at al

OVER- AND UNDERDETERMINED SOLUTIONS

With the linear model eq. (7.2) it is much easier to draw general con clusions. It was notably Tinbergen [153,154] who investigated essentially static and deterministic versions of the model. In the discussion of his target approach, he classified solutions of eq. (7.2) expressing the policy or decision variables $\underline{\Theta}_t$ as a function of preassigned target values $\underline{Y}_t$ of the endogenous variables. As normally with linear algebraic systems, h

distinguished between exactly determined solutions, an infinite number of solutions or the case, where no solution was possible (i.e. an overdetermined solution). It was also seen that "What-if?" type investigations, as are most frequently carried out by corporate modelers today, correspond to a solution of eq. (7.1 - 7.2) expressing the endogenous variables $\underline{Y}_t$ as a function of preassigned values of the decision variables $\underline{\Theta}_t$. A number of authors, notably Theil [152], have investigated such solutions. Similarly as in Tinbergen's target or "What to do to achieve?" analysis one may again distinguish model solutions dependent on whether there is exactly one solution, an infinite number of solutions or no solution whatsoever. All three cases have been discussed quite extensively by Theil [152, pp. 372-527] mainly for linear static and stochastic systems. He states that Tinbergen's approach is not altogether satisfactory, especially for overdetermined or underdetermined model solutions: In the case that the number of targets exceeds the number of decision variables, all the targets are frequently not reached simultaneously in a model solution (viz. also Tinbergen [152, pp. 114-139]). An infinite number of solutions results if the number of decision variables exceeds the number of endogenous variables or targets. The same values of the endogenous variables may then be obtained for various combinations of the decision variables. Theil's analysis under these circumstances is based on the maximization of a utility func-

$$w = w\,(\underline{Y}_t,\ \underline{\Theta}_t) \tag{7.3}$$

tion under the constraints eq (7.1) or (7.2), i.e. he assumes that the decision maker is able to rank alternative model solutions according to increasing preference. The most likely decision then is the one that gives greatest satisfaction or maximum utility to the decision maker-even if the targets are not completely attainable. Theil's and similarly Contini's [41] analysis is beyond that more general than Tinbergen's original analysis, because they also allow for uncertain model parameters or equations through the introduction of additive stochastic disturbances. Maximization of expected utility or the use of certainty equivalents could be one suitable substitute for the maximization of utilities under these circumstances (viz. von Neumann, Morgenstern [127], Fishburn [60], Keeney, Raiffa [99]). In any case the model will possess some sort of "... inbuilt pain and pleasure response (viz. Churchman [37, p. 10])".

CRITICISM OF OPTIMIZATION APPROACH

In chapter 1 the relation between the objectives of corporate modeling and goals and objectives of the firm was discussed. The concept of the profit maximizing firm of the classical theory has come under severe attack since the behavioral and organizational theories (viz. Cyert and March [42], Simon [141], Naylor [120]) investigated the process by which and by whom decisions were reached in the firm (viz. Ackoff [3]). These findings were supported by empirical research (viz. e. g. Hall and Hitch [70], Heinen [79[, Eliasson [56], Hamel [71], Hauschildt [77]) and lead to the formulation of target, satisficing, aspiration level and robustness goals and objectives for the firm and its members. As a consequence of this discussion there is also a tendency to discard the optimization approach from corporate modeling. The surveys by Grinyer and Wooller [68] and Naylor and Schauland [123] indicate that only few purely optimizing corporate models exist in practice.

At first, these findings seem to sharply contrast with Theil's utility maximization concept. But one should analyze where the differences in viewpoint actually come from: "There can be no doubt that it (i.e. a satis ficing policy (author)) is sometimes attractive for a description of "actual" behavior; it is even conceivable that is appropriate for "rational" behavior under certain circumstances. Nevertheless, it is important to make a distinction between the reduction of attainable welfare (or profits utility and other endogenous variables (author)) due to imperfect forecast and the reduction of actual welfare caused by the fact that the policy-maker is satisfied with less than the "attainable maximum" (Theil [152, p. 386]). The approach taken in real world decision making, but also modeling to a large extent depends on the available information. A number of authors have shown that the target, satisficing or flexibility and robustness approach to decision making may be cast into the form of a maximization approach provided the information is relevant and reliable enough to construct and discriminate between alternative model solutions (viz. Rosenhead et al. [132], Jacob [95], Dinkelbach [50]). A selection mechanis or optimization algorithm may then be employed for a model of the problem. Instead of using the model as an "alternative tester" it is used a "alternative selector" (viz. Dickson et al. [47, p. 59]).

The most pragmatic approach to a discussion of the question whether a corporate model should only generate feasible solutions or if feasible

solutions should be selected and ordered with an inbuilt mechanism is perhaps to center the discussion around the answers to the following two questions: first, is the model useful for decision making, second, is a certain solution feasible from a computational viewpoint?

The literature contains a number of corporate model descriptions for which optimization methods were at least used with submodels. In the following sections and chapter 9 some additional examples will be given. These examples mainly deal with operative planning models in the areas of production [2, 9, 46, 55, 78, 118, 150, 86, 87] or finance [25, 26, 34, 94, 104, 145]. Optimization models to support the strategic planning process are found less frequently (e.g. [74, 75, 145]). In total there are no reasons which speak against the use of optimization or stochastic models for corporate planning applications. The fact that most models are of the deterministic "What-if?" type may either be explained by the observation that the planning problems described are badly structured and do not justify the selection of solutions or due to computational difficulties. The use of optimization techniques may furthermore be combined with the simulation approach (viz. e.g. [26, 86, 87]) and post-optimal sensitivity or parametric analysis may be understood as "What-if?" investigations. However, care should be taken that the flexibility of the "What-if?" type investigations is not sacrificed to an unrealistic adjustment of a problem and model to a special solution or optimization technique and objective (viz. Boulden [17, p. 2]).

TYPES OF OPTIMIZATION

The models so far described either seem to fit directly into the framework outlined by Theil (viz. Hamilton [73], Holt, Modigliani, Muth, Simon [89]) or make a slight generalization due to inequality or integrality restrictions on endogenous and decision variables necessary.

It is well known that inequalities may be transformed into equations by the introduction of suitable slack or proxy variables and sign restrictions on some of the model variables, say Θ_{1t}, $\Theta_{2}t$, ...Θ_{h^*t}, $h^* \leq h$, of the decision variables y_{1t}, y_{2t}, ...y_{k^*t}, $k^* \leq k$ of the endogenous variables. The optimization problem may then be formulated as maximize

(7.4) $$w_t = w\,(w_{t-1}, \underline{Y}_t, \underline{Y}_{t-1}, \underline{X}_t, \underline{\Theta}_t, v_t)$$

under the constraints eq. (7.1) or 7.2) and

(7.5) $\Theta_{it}, y_{jt} \geq 0$, $i = [1, h^*]$, $j = [1, k^*]$,

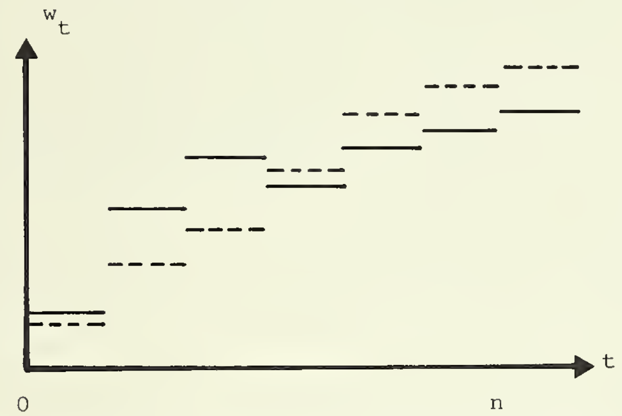
where v_t is an additional stochastic disturbance. As Theil [152, p. 386] has pointed out, these equations represent a general one-person game against nature with "random" moves.

Due to the stochastic nature of the model, pay-offs and utilities may have different realizations for given t, $\underline{X}_t$, $\underline{\Theta}_t$ and $\underline{Y}_{t-1}$. It has been pointed out before that under these circumstances one would instead for example try to maximize expected utilities or pay-offs or minimize the variance of deviations from target values.

It should be noted that some of the model variables may only attain discrete values, as occurs e.g. if one uses binary variables with non-conjunctive relations. Without loss of generality one may restrict oneself to maximization problems and greater than or equal to ($\geq$) restrictions. Also the utility or objective function may contain lagged terms of w_t and a separate stochastic disturbance v_t. The explicit formulation of eq. (7.4) does not imply a simplification of the model structure from a notational viewpoint. However, its formulation may create serious difficulties for practical computations. It should also be noted that eq. (7.4) does not give an indication for which time periods t, t = [1, n], an optimization has to be carried out. Two extreme cases could be distinguished. Either one optimizes for every period after previous values or expectations of w_{t-1}, $\underline{Y}_{t-1}$, especially w_0, $\underline{Y}_0$, have been supplied or calculated, or the optimization is carried out for one period, say t = n, only. In the former case previous decisions would not influence the determination of the present optimal decisions, whereas in the latter case one could observe a trade-off between the optimality of previous decisions and optimality of the final response w_n as it is shown in Figure 7.1.

It is easy to show that the optimal solutions will be identical in general only if either one deals with a one-period problem or if the model structure, including the objective function, does not contain any inter-period relations. In the other cases, one would expect the value of w_n that follows from a period to period optimization to be less or equal to the value obtained from a final value optimization. In the literature, the latter problem usually is referred to as the optimal control problem and is one of the main application areas of non-classical variational methods (viz. Bellman [11], Pontrjagin et al. [128], Hadley, Kemp [69], Intriligator [93], pp. 292-369], Arrow, Kurz [6], Bensoussan et al. [16]).

Figure 7.1. Period per period (-) versus final value (---) optimization



The system of equations (7.1 - 7.5) is much too general to allow the suggestion of a special solution method. However, two observations may be made: First, quite independent of the problem under investigation, it is very likely that the solution will to some extent be based on the Kuhn-Tucker theory of mathematical programming [105]. Second, as with all the model solutions so far discussed, the solution will be easiest with linear, static and deterministic systems. The computational costs increase rapidly whenever one has to take stochastic disturbances, non-conjunctive relations, non-linearities and a time dependency into consideration. With such models one very quickly either meets economic limits (e.g. computer time) or theoretical limits, because appropriate solution methods are not at hand at the present state of the art.

If optimization methods were at all employed with corporate models, in most cases linear programming was used. Two models are known to us in which searching techniques were applied [94, 145]. A number of authors have constructed nonlinear mathematical programming or optimal control models for either real world financial or marketing applications [4, 103, 111, 146] or for corporate models of fictitious firms [43, 73, 89, 116].

APPLICATIONS OF LINEAR PROGRAMMING

Classical linear programming applications are especially found in areas where scarce resources, such as production capacities, raw material supplies or financial means may be allocated to a large number of alternative activities. Resource requirements are usually formulated in the form of linear inequalities or equations, the cost or benefit associated with a certain solution is quantified by the linear objective function.

The linear programming approach incorporates several limitations as there are

- assumption of proportionality of the objective function and resource limitations to the levels of the individual model variables,
- the hypothesis of the additivity of the effects of different variables and their missing higher order interaction,
- the assumption of perfect divisibility of the model variables (viz. Wagner [158, pp. 33-163]).

The last assumption has been made operational due to the availability of efficient integer and mixed continuous-integer programming methods. [62, 14, 15].

Nearly all computer manufacturers today supply linear programming software which may either be attached to CSPSs which possess a language interface or be used in a separate task independently from the CSPS. The first integrated solution is of advantage especially for small models which do not require very refined and accurate solution methods. Source listing for simple linear programming algorithms are available from the literature (viz. Künzi, Tschach,Zehnder [106], Lee [110], Zeleny [165]) and linear programming macros may be incorporated among the statements of a CSPS. The CIBA-GEIGY COMOS contains the Revised Simplex and the Transportation Algorithm for this purpose.

The business oriented linear programming literature has been dealing for a very long time with problems of organizational decentralization and transfer pricing. Using the duality theorem and the decomposition principle of linear programming, optimal transfer prices between organizational units were determined by a number of authors. However, very little is known about real world applications of these investigations. Especially for larger multinational companies it seems that the assumptions of the linear programming approach are unrealistic if different tax, customs and government re-

gulation systems have to be dealt with simultaneously. Since several of especially the financial corporate models known deal with taxes and customs, it seems that mainly deterministic "What-if?" investigations provide the flexibility to treat such problems.

GOAL AND MULTIPLE CRITERIA PROGRAMMING

It has been noted above that more recently developed theories of the firm and a number of empirical investigations indicate that the questions of goals and objectives of the firm is indeed a very complex one. One of the conclusions following from these investigations is that the assumption of a uni-criterion objective or utility function for a total firm or its model is very likely to be a gross oversimplification. For example Lee [110, p. 10] quotes the results of an empirical investigation ranking as primary points of interest for the top management of 25 corporations in decreasing order of frequency: personnel, duties and responsibility to society in general, consumers' needs, stockholders' interest, profit, quality of product, technological progress, supplier relations, corporate growth and managerial efficiency. Only the fourth and fifth points resemble goals that were most frequently used with the first linear programming models and classical models of the firm (viz. Dorfman [51], Boulding [18], Förstner, Henn [61]). Of course one could argue that all these goals are only modifications of the classical long-range profit maximization objective, but it is more than questionable if this objective is operational with models of a rather limited time horizon or rapidly changing environment.

Due especially to the work of Charnes, Cooper and Ijiri [29, 31-33, 92, 160] it became clear that the mathematical, especially the linear programming approach was flexible enough to allow also for multicriterion utility or objective functions. Either an appropriate goalweighting was used in the objective function or the significance of goals and constraints was interchanged to some extent in these applications (viz. Eilon [54], Rosenhead et al. [132], Jacob [95]). The principle is perhaps best explained with a quotation from Charnes, Cooper, Ijiri [31, p. 17]:

"The pursuit of an optimum objective plays a prominent role in linear programming. But this does not mean that applications are restricted to situations where optimization has been stated as an actual managerial objective. A variety of artifacts are available for use when other objectives are at issue and some of these same artifacts may be used to handle various kinds of nonlinear (and stochastic (author)) problems via mathematical

models that are suitably arranged for applying any of the linear programming solution methods."

Although methods of goal and multi-criterion linear optimization have been known for more than twenty years, it seems that these methods have only very recently been applied more frequently in practice. Methodologically they seem to close the gap between Tinbergen's target analysis and Theil's optimization approach.

In chapter four an example was given to illustrate the use of "What to do to achieve?" questions in corporate modeling. In the example, a system of linear and deterministic model equations was graphically evaluated to satisfy two non-commensurable goals as closely as possible. One of the goals implied a minimization of deviations from a budgeted target profit, the second asked for maximum utilization of available plant capacity. It was assumed that the first goal had absolute priority over the second. This corresponds to a strong ordinal ranking of the utilities related to the attainment of the two goals. Utility differences were not defined. It was only assumed that no positive and real valued constant existed such that if the utility due to the attainment of the second goal was multiplied by that constant, the product could become equal to the utility due to the attainment of the first goal. In the section below a similar example derived from a real world case study will be described more explicitly.

The left hand sides of Figures 7.2 and 7.3 show the balance and income statement of a CIBA-GEIGY daughter company which were generated in the rolling five year planning. The figures have been distorted systematically. The problem consisted in a minimization of the deviations from planned profit-after-tax values \$ 82.000 in 1978, \$ 86.000 in 1979 and \$92. 000 in 1980 under consideration of certain financial ratios and constraints and different costs of financing. The right hand sides of Figures 7.2 and 7.3 show the results with changes in most of the positions of the balance and the profit and loss statement.

The linear programming model was made up for the following variables, parameters and equations:

Figure 7.2. Balance goal programming example

		BALANCE SHEET				Company Canada		
	Can. Dollar	Initial Solution				Goal Progr. Solution		
1976		1977	1978	1979	1980	1978	1979	1980
7400	1 Liquid Funds	8220	2240	2240	2240	29943	36041	42953
62720	2 Receivables	35660	37180	35140	38020	25249	26519	28295
74680	3 Inventories	76760	79840	81380	87860	46633	51545	67009
10480	4 Other Current Assets	12123	27575	37180	55540	27575	37180	55540
155280	5 Total Current Assets	132772	146835	155940	183660	129400	151285	193797
0	6 Short Term Bank Liab.	0	20740	24020	44120	0	0	0
8960	7 Accounts Payable	8960	8960	8960	8960	8960	8960	8960
115640	8 Other Sh. Term Liab.	115300	129020	147440	169160	129020	147440	169160
124600	9 Total Current Liab.	124260	158720	180420	222240	137980	156400	178120
30680	10 Working Equit. Cap.	8512	-11885	-24480	-38580	-8580	-5115	15677
161240	11 Fixed Assets	189112	204815	222620	232320	204815	222620	232320
15600	12 Other Long Term Assets	32260	53440	56580	72580	53440	56580	72580
176840	13 Total Long Term Assets	221372	258255	279200	304900	258255	279200	304900
24060	14 Long Term Bank Liab.	23720	22280	20840	19400	22289	31620	57796
720	15 Other Long Term Liab.	3104	34111	53320	90000	34111	53320	90000
24780	16 Total Long Term Liab.	26824	56391	74160	109400	56399	84940	147796
95655	17 Share Capital	119911	111276	103146	82781	111276	103146	82781
0	18 Reserves	0	0	0	0	0	0	0
0	19 Retained Earnings	0	0	0	0	0	0	0
87085	20 Profits	83149	78704	77414	74139	82000	86000	90000
182740	21 Total Eq. Capital Kons.	203060	189980	180560	156920	193276	189146	172781
332120	22 Total Assets	354144	405091	435140	488560	387655	430485	498696

Figure 7.3. Income statement, goal programming example

			INCOME STATEMENT				Company Canada		
		Can. Dollar	Initial Solution				Goal Progr. Solution		
1976			1977	1978	1979	1980	1978	1979	1980
350180	1	Sales	360380	373562	387220	406450	378123	409202	450532
72775	2	Var. Product Costs	75931	84658	93266	103090	85691	98560	114271
17520	3	Var. Division Expenses	17000	18960	18320	18800	19192	19360	20839
259885	4	Marginal Contribution	267449	269944	275634	284559	273240	291282	315422
117660	5	Div. Period Costs, Exps.	126180	134220	141240	150020	134220	148302	165022
142225	6	Div. Contrib. Bef. Servs.	141269	135724	134394	134539	139020	142980	150400
		Function Expenses							
0	7	Fcr. Cap. Interest	700	1340	1860	2620	1340	1860	2620
380	8	Interest Proc. Third Part.	0	0	0	0	0	0	0
0	9	Exchange Rate Diff.	0	0	0	0	0	0	0
0	10	Extracrd. Pens. Contrib.	0	0	0	0	0	0	0
40220	11	Other Funct. Expenses	40560	41240	42600	44040	41240	42600	44040
40600	12	Total Funct. Expenses	41260	42580	44460	46660	42580	44460	46660
19100	13	Service Analysis	20940	21560	22540	23320	21560	22540	23320
21500	14	Funct. Exp. After Serv.	20320	21020	21920	23340	21020	21920	23340
120725	15	Contribt. Bef. Tax	120949	114704	112474	111199	118000	121060	127060
		Intercomp. Transact.							
0	16	Invisible Expenses	0	0	0	0	0	0	0
0	17	Invisible Income	0	0	0	0	0	0	0
0	18	Prov. For Taxes	0	0	0	0	0	0	0
0	19	Other Intercomp Transact.	0	0	0	0	0	0	0
0	20	Total Intercomp. Transact.	0	0	0	0	0	0	0
120725	21	Profits before Tax	120949	114704	112474	111199	118000	121060	127060
33640	22	Proc. Tax	37800	36000	35060	37060	36000	35060	37060
87085	23	Profits after Tax	83149	78704	77414	74139	82000	86000	90000

Variables

yB_{it}, xB_{it}	Balance Variables of New Solution and Initial Solution respectively, i = [1, 29], t = [1978, 1980]
yI_{jt}, xI_{jt}	Income Statement Variables of New Solution and Initial Solution, j = [1, 35], t = [1978, 1980]

Especially of interest for the model are

yI_{1t}	Sales to Third Parties
yI_{2t}	Variable Product Costs
yI_{3t}	Variable Divisional Expenses
yI_{4t}	Marginal Contribution
yI_{5t}	Period Costs and Expenses
yI_{23t}	Profits after Taxes
yB_{1t}, xB_{1t}	Liquid Funds
yB_{2t}, xB_{2t}	Receivables
yB_{3t}, xB_{3t}	Inventories
yB_{6t}, xB_{6t}	Short Term Bank Credits

xB_{7t}	Accounts Payable
xB_{8t}	Other Short Term Liabilities
yB_{14t}, xB_{14t}	Long Term Bank Credits
$yB_{20t} = yI_{23t}$, xB_{20t}	Profits after Taxes
yT_t	Target Profit
yD_t^+ , yD_t^-	Positive and Negative Deviations from Target Profit
yO_t	Objective Variable

Parameters

$Q_1 = 0.1$	Lower Limit of Quotient Receivables/Sales
$Q_2 = 0.2$	Upper Limit of Quotient Receivables/Sales
$Q_3 = 0.5$	Lower Limit of Quotient Inventories/Variable Product Costs (One Period Ahead)
$Q_4 = 0.75$	Upper Limit of Quotient Inventories/Variable Product Costs (One Period Ahead)
$Q_5 = 0.25$	Liquidity Coefficient (Quick Ratio), Lower Limit
$Q_6 = 0.4$	Liquidity Coefficient (Quick Ratio), Upper Limit
M_1	Goal Weighting Factor for Financing and Current Assets
M_2	Goal Weighting Factor for Profit Goal Deviations
$C_1 = 0.06$	Interest Rate for Liquid Funds
$C_2 = 0.06$	Interest Rate for Inventories
$C_3 = 0.1$	Interest Rate for Short Term Bank Credits
$C_4 = 0.06$	Interest Rate for Long Term Bank Credits

Inequalities and Equations

Bookkeeping identities which are either self-explanatory or which correspond to the examples given in chapter four have been omitted.

Sales-Receivables

(7.6) $$Q_1 \cdot yI_{1t} \leq yB_{2t} \leq Q_2 \cdot yI_{1t}$$

Inventories-Variable Costs

(7.7) $$Q_3 \cdot yI_{2(t+1)} \leq yB_{3t} \leq Q_4 \cdot yI_{2(t+1)}$$

Liquidity

(7.8) $$Q_5 \cdot (xB_{7t} + xB_{8t}) \leq (yB_{1t} + yB_{2t} - Q_5 \cdot yB_{6t})$$

(7.9) $$Q_6 \, (xB_{7t} + xB_{8t}) \geq (yB_{1t} + yB_{2t} - Q_6 \cdot yB_{6t})$$

Profits

(7.10) $$yB_{2ot} + yD_t^+ - yD_t^- - yT_t = 0$$

Balance Equality

(7.11) $$(yB_{1t} - xB_{1t}) + (yB_{2t} - xB_{2t}) + (yB_{3t} - xB_{3t}) - (yB_{20t} - xB_{20t}) - (yB_{6t} - xB_{6t}) - (yB_{14t} - xB_{14t}) = 0$$

Variable Costs

(7.12) $$yI_{2t} = yI_{1t} \cdot \frac{xI_{2t}}{xI_{1t}} \; ; \; t = 1978, 1979 \; ; \; yI_{2(1977)} = xI_{2\,(1980)}$$

Variable Expenses

(7.13) $$yI_{3t} = yI_{1t} \cdot \frac{xI_{3t}}{xI_{1t}}$$

Period Costs and Expenses

(7.14) $$yI_{5(1975)} = xI_{5(1978)} \; ; \; yI_{5(1979)} = 1.05 \cdot xI_{5(1979)} \; ; \; yI_{5(1980)} = 1.1 \cdot xI_{5(1980)}$$

Sales-Profits [1]

(7.15) $$yI_{1t} = (xI_{4t} + (yB_{20t} - xB_{20t}) - (yI_{5t} - xI_{5t})) \,/\, \left(1 - \frac{(xI_{2t} - xI_{3t})}{xI_{1t}}\right)$$

Objective Function

(7.16) $$yO_t = M_1 (C_1 \cdot yB_{1t} - C_2 \cdot yB_{3t} - C_3 \cdot yB_{6t} - C_4 \cdot yB_{13t}) - M_2(yD_t^{+} + yD_t^{-}) \rightarrow \text{Max} \; ; \; M_1 \ll M_2$$

With eq. (7.7) the model contains only two inter-period constraints relating inventories by value in period to to forecasted variable costs in period (t + 1). Due to this property the solutions were generated backwards estimating variable costs in 1981 to be equal to the original planned variable costs in 1980. Although interest rates show up in the objective function eq. (7.16) for the sake of simplicity they are not taken care of in the income statement.

The objective function eq. (7.16) contains two non-commensurable goals: Deviations from a planned profit value are weighted with a constant M_2, the terms of the objective function that describe preferences with

respect to different modes of financing and capital tied in current assets are weighted with a constant M_1, where $M_2 >> M_1$. The two main goals are so called 'pre-emptive' goals (viz. Charnes, Cooper [29], Ijiri [92], Lee [110, 139], Contini]41]). It is assumed that no positive and real valued constant g exists such that $M_1 = g \cdot M_2$. Thus, the problem actually is solved with separate objective functions as is usually done to eliminate artificial variables from the basis of a linear program (viz. Dantzig [44], Wagner [158]). A similar approach may be chosen with more complex models whenever goals or targets may be ranked in a hierarchical fashion. Goals or targets may not only be derived for the financial segment of a corporate model, but also for the production and marketing segments. Examples could simultaneously be output maximization, scrap and idle capacities minimization for the production area, personnel wage and market share satisfaction and advertising and distribution costs minimization for the marketing area (viz. [10], [139]). In practice pre-emptive goal weights are subjectively supplied by the model user who performs $\frac{1}{2}$ m (m-1) utility comparisons if the model is to contain m non-commensurable and hierarchical goals. Commensurable goals may be treated by the linear programming approach especially on one hierarchical level. The objective function eq.(7.16) is an example for such an application. Interest rates C_1 to C_4 are used to express the desirability for liquid funds, inventories short and long term bank credits in a model solution. Of course, the weights M_j, j = [1, m] could also be expressed numerically. This would then correspond to the case of cardinal utilities with the effect that - due to the model restrictions eq. (7.6 - 7.15) - a trade-off between the utilities of different goals becomes possible. Their numerical determination will often lead to complicated problems of scale and measurement (viz. Fishburn [60], Keeney and Raiffa [99]). Also non-linearities and multivariate probability distributions for goal attainment are more likely to be used (Simon [142], Charnes Cooper [32, 33], Theil [152], Contini [41]). So far only work on linear deterministic problems with multi-criterion objective function seem to be well enough developed for use in corporate modeling. Roy [135] and Zeleny [165] give a survey and a selected bibliography for problems and solutions with multiple goals and objective functions. Roy distinguishes especially the following four approaches to solve problems of this nature:

1. Aggregation of multiple objective functions in a single function defining a complete preference order. Goal programming, but also methods in which goal weights are a priori and numerically specified, belong to

this approach.

2. Progressive definition of preference during a model solution together with an exploration of feasible, effective or Pareto optimal solutions (viz. Geoffrion [63, 64, 66], Roy [135], Benayoun et al. [14], Fandel [58], Belenson, Kapur [10], Vincke [157]).
3. Definition of partial preference order that is stronger than the product of the n complete preference orders associated with n ojbective function.
4. Maximum reduction of goal uncertainty and imcomparability (viz. Charnes, Cooper [32], Contini [41]).

It is surprising to recognize the similarities especially between the second approach and the type of behavioral and organizational model of rational choice that has been advocated by Simon [141] already some twenty year ago. An "optimal" or "efficient" solution (viz. Charnes, Cooper [32], Geoffrion [64], for a multi-criterion problem has to be something like a "best compromise" between all objectives. To achieve this compromise, trade offs between objectives have to be assessed subjectively. One can imagine a variety of circumstances under which the model user will only be able to make such comparisons after he knows the consequences of his preference decisions with respect to the values of the model variables. Therefore, the model user would specify his goal preferences in practical computations only after the modeling system has generated some propositions for a solution. In successive iterations the model user would define his preferences in parallel to the optimization process. Computationally, the approach seems to ask for the sequential solution of mathematical programs in an interactive manner. Some practical applications of the approach are already known [14, 66] and it will probably not be very long before it will be used and offered with corporate simulation and planning systems.

NON-LINEAR AND STOCHASTIC PROBLEMS

While the corporate modeling literature in the meantime contains several examples which indicate that linear programming methods may successfully be applied in the practice of corporate modeling, only two references are

known to us that indicate an application of non-linear optimization methods.

In their description of the financial simulation model of the ICI Heavy Organics Division Jackson et al. [94] formulate a dynamic and non-linear objective function for their model. It may be denoted as a "Shareholders Return" function and incorporates dividends and differences between share purchase and selling prices. The latter are determined based on the assumption that stock-market prices are directly proportional to the sum of retained earnings. The optimal response of the objective function to various policies is determined with a search strategy that, it seems, changes one variable at a time. Springer [145] reports on the application of searching methods to the General Electric PROM model. As far as one can deduce from this evidence, the objective functions of both models were deterministic like the rest of the model structure and inequality restrictions were not dealt with. The following lines are intended to give some indications and references as to which optimization techniques are available for the solution of the general optimization model eqs. (7.1 - 7.5). Since several non-linear and even stochastic corporate models for ficticious firms are known that use non-classical variational methods as a solution technique, these are more explicitly described later in this chapter.

As many researchers have noted before, such properties as model size (i.e. number of equations) and model structure are in many instances closely interrelated from the point of view of model solution [65]. Since nowadays most firms have access to computer software that enables them to solve large systems of linear algebraic equations and inequalities, more complicated models that are dynamic, incorporate stochastic disturbances, non-conjunctive relations and non-linearities may be manipulated in such a way that they become accessible to linear solution methods. A local linearization of the equations and objective function of a model is the main technique used and inequalities and sign restrictions on model variables as well as an increased model size may only be the consequence of such a linearization.

UNCERTAINTY

Models that contain stochastic disturbances have been transformed into extended mostly non-linear deterministic models in a number of investigations. Chance was incorporated into the structure of these models by either introducing new restrictions to take different realizations of random variables into account or by modifying the objective function by the introduction of costs of uncertainty or certainty equivalents. In some well known examples the latter approach resulted in linear or non-linear fractional or quadratic programs (viz. Tintner [155], Charnes, Cooper [30, 32], Balintfy [8], Dinkelbach [48], Swarup [148], Markowitz [114], Litaer [111], Vajda [156], Contini [41], Kall [97]). A satisficing or optimizing approach has been chosen in these models, e.g. Charnes and Cooper [32] discuss three types of models in which either the expected utility or payoff w_t (eq. 7.4) was maximized, the variance of a target utility was minimized, or, last but not least, the probability that the payoff would be greater than or equal to a target value or utility aspiration level was maximized.

SEARCHING METHODS AND EXPERIMENTATION

Linear and non-linear programming models mostly work with explicitly given objective functions and stochastic disturbances. However, in a corporate model, the response w_t may only be defined implicitly by a great number of possibly non-linear and stochastic equations. The model user determines the values of his decision variables. The actual model structure and mechanism that generates values and derivatives as they are needed for many non-linear programming algorithms is a 'black-box' to him. Furthermore, model linearizations as they have been described above could either be intractable and time consuming or may result in a model that describes another dynamic mechanism than originally intended. Under these circumstances, more experimental and heuristic optimization methods may be of interest.

If an extremum of the general objective function eq. (7.4) is saught for by computer experimentation, this could be achieved by simultaneous or sequential experimentation or by a combination of the two [161]. In the

first case one would design the experiments, i.e. determine the values of the decision variables and the number of experimental replications of the stochastic disturbances, without taking the results of other experiments with different values of the decision variables into consideration. On the contrary, in a sequential experiment one would, except in the very first experiment, determine new experiments on the basis of the experiences obtained from old experiments.

RANDOM EXPERIMENTATION

Since computer experiments as such are carried out sequentially, one obviously does not use the information about the location of the optimum generated during the experimentation when applying a simultaneous strategy. Still under various circumstances, one will prefer a simultaneous search strategy, especially a random search, to a sequential strategy. This will notably be the case if the response w_t eq. (7.4) is not a unimodal function of the decision variables and if the number of computer experiments has to be kept small. If nothing is known a priori about the response surface eq. (7.4), as frequently happens in exploratory optimization experiments, a random search that assigns equal probabilities to different realizations of the decision variables will with a small number of experiments be more likely to produce values of w_t close to the extremum than a sequential search. In most cases, one will be able to specify lower and upper bounds for the components of $\underline{\Theta}_t$. A random search in which every realization of $\underline{\Theta}_t$ is replicated a specific number of times to give estimated values of the expectation and variance of w_t will then yield a highest result that can be used as an approximation to the global extremum for further investigations, perhaps now using a sequential search strategy (viz. Nemhauser [125, pp. 139-204]). A random search will also supply information about other either local extrema or the global extremum and will indicate regions of the response surface which should be investigated more carefully. Although a random search will be very inefficient whenever the coordinates of the optimum have to be determined more accurately, the strategy supplies more rough information about the locations of the global extremum than the available sequential search strategies. For a small number of available experiments, this is even likely to be true for unimodal

response surfaces, because supplementary experiments necessary with these strategies to give an indication of response improvement may be great in number and time consuming (viz. Smith [143]). Furthermore, using the available random number generators, a random search is easy to program and flexible enough to often also allow for only discretely defined variables and variable restrictions.

SEQUENTIAL EXPERIMENTATION

In the case that one has obtained sufficient knowledge about the response surface either a prioi or after some exploratory experimentation one may want to determine the location of the extremum of the response function more accurately. Especially for unimodal and unrestricted response surfaces there exist a number of approximation and search strategies which may easily be applied in practice (viz. Himmelblau [83] for a comparison). Based on some results of Dvoretzky [53], Kiefer and Wolfowitz [100] and Wilde [161, pp. 181-183] present a multivariate extension of the Kiefer and Wolfowitz procedure. A very robust and easy to use multivariate direct search algorithm is due to Hooke and Jeeves [90]. It is described in the next section and may easily be implemented as a macro instruction of a CSPS. It has been used for the optimization experiment described below and is available in the CIBA-GEIGY system COMOS.

HOOKE-JEEVES ALGORITHM

Let the response surface be described by

(7.17) $$w = f(\underline{x}) \quad ,$$

where w is the response variable and $\underline{x}$ denotes a k-component vector of variables or factors which may be controlled in a computer experiment. Assume that the maximum of w is to be determined and that $f(\underline{x})$ is unimodal.

With the Hooke-Jeeves method two search strategies, so called exploratory moves and pattern moves are used sequentially. Starting with an initial vector $\underline{x}_0$ and function value f_0, the coordinats or variables x_i, i = [1, k] are one at a time successively changed by increments $\pm \Delta x_i$, i.e.

$x_i := x_1 - \Delta x_i$, $x_i := x_i - \Delta x_i$. If in one of these exploratory moves a higher function value is obtained, $\underline{x}_0$ is adjusted to this new value and the exploratory moves are continued with the remaining variables. The exploratory moves terminate if all variables have been considered in both directions $\pm \Delta x_i$. If a greater value of f $(\underline{x})$ has been obtained $\underline{x}_0$ and f_0 are replaced by $\underline{x}_1$ and $f_1 > f_0$. In the opposite case, the step-widths Δx_i are consecutively divided by a factor larger than one (two in the following algorithm) until either by a continuation of the exploratory moves a $f_1 > f_0$ with $\underline{x}_1$ is found, or the Δx_i become smaller than a preassigned limit ε. In the latter case, it is assumed that the maximum has been found.

In the first case a pattern move to

$$\underline{x} = \underline{x}_1 + \Delta\underline{x}, \ \Delta\underline{x} = \underline{x}_1 - \underline{x}_0 \tag{7.18}$$

is performed and the explanatory moves start again until an $\underline{x}_2$ with $f_2 > f_1$ is obtained. The next pattern move would be to

$$\underline{x} \equiv \underline{x}_2 + \Delta\underline{x} = 2\ \underline{x}_2 - \underline{x}_1 \ . \tag{7.19}$$

A graphical visualization of the vector additions and subtractions performed in eqs. (7.18) and (7.19) gives a good impression of how fast successful moves along a "normal coordinate" of the surface eq. (7.17) can be accelerated. On the other hand, the reduction of the step-widths in unsuccessful exploratory moves gives a good impression of how the direction and length of pattern moves can be turned and decelerated as is needed to follow curves in the surface. A disadvantage of the method is that the increments Δx_1 are only reduced, never increased during the iterations. This can bring about a rather slow convergence of the iterations if -after a curve in the surface has been passed- the pattern steps have to be increased again.

The following algorithm describes the method more explicitly:

Step 0: Define initial vector $\underline{x}_0$ and calculate f_0. Define $\Delta\underline{x} = (\Delta x_i)$, $i = [1, k]$. Let the iteration number e be $e = 0$ and define a vector $\hat{\underline{x}} = \underline{x}_0$. Let SWITCH = 1.

Step 1: Exploratory move: Calculate an $\bar{\underline{x}} = (\bar{x}_i)$, $\bar{x}_i = \hat{x}_i = \pm \Delta x_i$, $i = [1, k]$. In the case that a f $(\bar{\underline{x}}) > $ f $(\hat{\underline{x}})$ is found, let $\hat{\underline{x}} = \bar{\underline{x}}$, f $(\hat{\underline{x}})$ = f $(\bar{\underline{x}})$ and continue with next variable until $i = n$. If the exploratory move has been successful, let $e := e + 1$, $\underline{x}_e = \hat{x}$, f_e = f $(\hat{\underline{x}})$ and continue with Step 2. In the opposite case: Provided SWITCH=0 let $\hat{x}=\underline{x}_e$, SWITCH=1 and continue with Step 1. Otherwise, continue with Step 3.

Step 2: Pattern move: Calculate $\hat{\underline{x}} = 2\underline{x}_{e-1} - \underline{x}_{e-1}$ and $f(\hat{\underline{x}})$, let SWITCH = 0 and continue with Step 1.

Step 3: Decrease step-widths. Calculate $\Delta\underline{x} := 1/2\ \Delta\underline{x}$. If $\Delta x_1 > \varepsilon$ continue with Step 1, otherwise STOP.

More recent work on optimization experiments indicates that sequential search strategies that have been applied to non-linear deterministic problems (viz. [21, 85, 139]) may with some modifications also be applied to non-linear stochastic problems. In the pioneering work of Box and Wilson [19, 23] a steepest ascent type search strategy was combined with various experimental designs as they have been indicated in chapter 6 to calculate a local approximation to the response surface by multiple linear regression (viz. Davies [45, pp. 495-578], Cochran and Cox [38], Burdick, Hunter and Naylor [23, 121, pp. 165-184], Kleijnen [101], Smith [143]). Very likely other gradient and also non-linear approximation strategies could be used in a similar fashion. Spendley, Hext and Himsworth [144] discuss the so called "Simplex" direct search strategy (not to be confused with the Simplex method of Linear Programming). The improvements of this strategy due to Nelder and Mead could also be applied to stochastic problems. Meier [124] and Meier, Newell and Pazer [117, pp. 313-330] have applied a Simplex search to the optimization of an inventory system. Also the Hooke and Jeeves algorithm described above could be used for the same purpose. Only expected values of the response would have to be calculated with sufficient accuracy at the trial points to allow hypothesis testing between the expected values of different trial points. One would thus obtain information regarding further improvement of the expected response or other objectives empirically.

SEARCHING WITH CONSTRAINTS - EXAMPLE

Not much is known about the application of the above mentioned searching procedures to constrained non-linear and even stochastic problems (viz. Atkinson [7], Heller, Staats [80], Hesse [81]). However, it seems that especially the penalty function approach advocated by some authors (viz. e.g. Caroll [27], Bracken, Fiacco, McCormick [22, 59, 164], Wolfe [163], should allow the application of robust and versatile methods which have originally been developed for unconstrained optimization problems. This

may be illustrated by the following deterministic example which uses the Hooke-Jeeves algorithm described above.

Assume a three period two product planning problem which is characterized by the following profit function.

(7.20) $$y_{1t} = p_{1t} \cdot q_{1t} + p_{2t} \cdot q_{2t} - c_{1t} - c_{2t},$$

where the first two terms describe sales revenues for given prices p_{1t}, p_{2t} and product quantities q_{1t}, q_{2t}; c_{1t}, c_{2t} represent costs associated with the production of q_{1t}, q_{2t}.

Let

(7.21)
$$\begin{aligned} p_{1t} &= 20 \,.\, 1{,}04^{(t-1)} \,.\, q_{1t}^{-1/2} \\ p_{2t} &= 18 \,.\, 1{,}10^{(t-1)} \,.\, q_{2t}^{-1/3} \\ c_{1t} &= 1{,}20^{\,(t-1)} \,.\, (50 + q_{1t}) \,. \\ c_{2t} &= 1{,}15^{\,(t-1)} \,.\, (70 + 2\, q_{2t}) \end{aligned}$$

These price-demand and cost functions are consistent with classical cost and production theory. Their explicit time dependence describes e.g. inflation effects.

Assume that production is restricted by the following inequality constraints

(7.22)
$$\begin{aligned} q_{11} &\geq 30 \\ q_{22} &\leq 60 \\ q_{11} + q_{21} &\geq 100 \\ q_{13} \,.\, q_{23} &\leq 255 \end{aligned}$$

and $q_{it} \geq 0$ $i = [1,2]$; $t = [1,3]$. Let the objective function be

(7.23) $$w_t = w_{t-1} + y_{1t}$$

where $w_0 = 0$ and w_3 should be maximized. The model described by eq. (7.20) (7.23) defines a non-linear programming problem and a variety of specific techniques may be used to solve it more efficiently than by direct searching. However, not much knowledge about such techniques from the user's sid is required if a Hooke-Jeeves search is directly applied.

An unrestricted optimization problem is obtained if instead of eq. (3.5.20) the following non-conjunctive relation is employed

(7.24)
$$y_{1t} = \begin{cases} -\,M & \text{if restrictions are violated} \\ p_{1t} \cdot q_{1t} + p_{2t} \cdot q_{2t} - c_{1t} - c_{2t} & \text{else,} \end{cases}$$

where M is a large positive constant which creates a 'reflecting boundary' whenever search steps leave the feasible solution area defined by eq.

(7.22). Figure 7.4 shows the initial values chosen for the optimization experiment together with the optimal values of the variables. With $M=10^6$; $\varepsilon = 0.1$ and $\Delta q_{it} = 0.5$, $i = [1,2]$, $t = [1,3]$ it took 266 iterations to obtain the optimum.

Figure 7.4 Solution to Nonlinear Programming Example

	Optimal Values		Initial Values	
t	q_{1t}	q_{2t}	q_{1t}	q_{2t}
1	100	216	100	20
2	75	60	40	10
3	3	85	10	25

Optimum $w_3 = 376$

One could well imagine that the parameters in eq. (7.21) have been obtained from a statistical estimation. Information about stochastic disturbances would thus be available from the estimation step and the example could be formulated as stochastic optimization problem. Experimental design techniques discussed in chapter 6 could be combined with the searching method mentioned above.

This combination of optimization methods for deterministic models with experimental design techniques should have one main advantage over methods of stochastic programming that work with explicitly given objective functions (viz. Tintner [155], Charnes, Cooper [32], Vajda [156], Balintfy [8], Kall [97]): The approach would not require a particular objective function and would be applicable to a wide class of objective functions, constraints and stochastic disturbances. However, it has to be investigated whether this advantage is not for many problems offset by the costs of experimentation, even if variance reduction methods are used (viz. Hammersley, Morton [72], Moy [119], Kleijnen [101], Rosenkranz [134]).

OPTIMAL CONTROL PROBLEMS [2]

The final value optimization or optimal control problem was previously formulated as the problem of maximizing the final value w_n of the objective function eq. (7.4) under the constraints eq. (7.1 or 7.2) and eq. (7.5).

THEORETICAL INVESTIGATIONS

The literature contains various examples for special solutions of this optimal control problem. Theil [152, pp. 415-527] discusses a static or one period example in which the linear restrictions eq. (7.2) may be expressed as a function of the endogenous variables $\underline{y}_t$ (i.e. B^{-1} exists) and the stochastic disturbances $\underline{U}_t$ have zero expectation and a finite variance-covariance matrix. The latter is independent of the decision variables. The pay-off or utility function is deterministic, strictly concave and contains only linear and quadratic terms of the endogenous and decision variables (Intriligator [93, p. 299]). A simple form of this objective function would for example be obtained with a satisficing strategy whenever negative quadratic deviations from target values are maximized. Ijiri [92] discusses completely deterministic models of a similar kind, but containing inequalities. Finally, Contini [41], formulates Theil's stochastic model including inequalities as a quadratic programming problem. While Theil maximizes the expected value of w_t, Contini instead maximizes the probability that the endogenous variables $\underline{y}_t$ are contained in an elliptical confidence region.

A dynamic generalization of Theil's model is due to Simon [142]. Using a simple production-, sales- and inventory-model and dynamic programming, he showed that maximizing expected utilities could be achieved using certainty equivalents or expected values for the random variables. A similar result has been obtained by Krouse [104] for a dynamic corporate financial model of a ficticious firm with quadratic objective function as well. In contrast to Simon, he allowed some elements of the matrices in eq. (7.2) to be time dependent. For stochastic linear models, quadratic utility function and constraints on the decision and endogenous variables he suggested an application of the discrete maximum principle (viz. Katz [98], Fan, Wang [57], Holmes [88], Benavie, Gould [12]) together with a Hooke-

Jeeves search.

In all the models mentioned so far, it was assumed that the model structure, model parameters and distribution of stochastic disturbances were determined before the optimization was carried out. In practice this would be the case only after alternative models have been discriminated and estimated. Thus, parameters and disturbances in a stochastic model could for example, be derived from an estimation of the "best" model using multiple regression techniques. An optimization that is independent of previous steps in the modeling design procedure obviously overlooks all reasons and consequences that different sources of random variation may have. As such stochastic disturbances may be introduced due to a true stochastic behavior of some model components, measurement errors or specification errors. Hauptmann [76, pp. 90-99] discusses a continuous stochastic and linear model with quadratic utility function that deals with the joint problem of estimation and optimization and employs the theory of optimal linear filters with non-classical variational methods. His approach is limited to equality constraints in the form of stochastic linear differentials. Prescott [130] discusses a discrete control problem in which again a quadratic pay-off function is maximized or minimized under equality constraints. These are given in the form of a system of linear regression equations only containing endogenous and decision variables. Inter-period relations are only included in his model due to the observation that in a model with uncertain parameters and stochastic disturbances further information regarding the parameters is obtained from experimentation with the model. He is able to demonstrate that a control policy combining the steps of estimation, experimentation and optimization may be superior to a policy using certainty equivalents, such as expected values, for the model parameters. Similar research has more recently been carried out by Chow [35, 36] and Mac Rae [112]. For unconstrained optimization problems dealing with the joint problems of model discrimination, estimation, experimentation and optimization, the work of Box and Wilson [19,20], Hill, Hunter and Wichern [82] and Spendley, Hext and Himsworth [144] should be mentioned.

PRACTICAL APPLICATIONS

While the number of theoretical publications on the use of optimal control techniques in economics is indeed large in number, little is known

about applications in practice. Probably optimal control techniques will be among the most satisfactory, when it comes to the control of an economy or a firm and keeping the economic system on or above targets as is advocated in dynamic concepts of the optimizing, satisficing or adaptive firm. But since a model of such a system is most likely to be characterized by a great number of possibly non-linear and partially stochastic algebraic or difference equations, at the present state of the art there just do not seem to be techniques available to deal economically with problems of such a complex nature. Furthermore, the problem of data collection model identification and estimation has so far largely been neglected in discussion of the optimization of dynamic and discrete systems.

Very few examples are known that actually indicate the practical use of discrete optimal control techniques: In a study of inventory and distribution problems connected with the sales of Israeli citrus fruits in Europe, Kohn and Plessner [103] present a discrete optimal control model which was designed for decision making. The uncertainty in the demand fore casts was not treated analytically in this model, but restrictions on the decision variables (sales of groups of fruits in different countries) were introduced to guarantee a satisfactory inventory level. The deterministic model was solved using the discrete maximum principle together with the Regula Falsi to evaluate the Kuhn-Tucker conditions [105]. Much the same techniques are used in the corporate modeling application that is describe below. The main difference between the two models from a methodological point of view is due to the explicit consideration of stochastic disturbances in the latter model. The optimization model together with its links to the income statement and balance sheet of a CIBA-GEIGY daughter company are described in the sequel. A more extensive description of the solution methods employed may be found in [134]. The model is based on real data. These have systematically been distorted in the following example. However the model was only intended as a feasibility study and has not been used i practice.

In Figure 7.5, a GESIFLOG-representation of the model is given. It consists of a system of recursive, but partially nonlinear difference equa tions. The equation number has been noted on the corresponding arcs for no linear relations. Some of the arc transmittances may be understood as random variables.

The model describes profits y_{4t} of an inventory, production and sales system as a function of time y_{1t} - here treated as an endogenous state var

able - and raw and finished products inventory level y_{2t}, y_{3t}. State changes are caused by the evolution of the system and the decision variables Θ_{1t} (selling price), Θ_{2t} (quantity produced) and Θ_{3t} (purchased quantity of raw products).

Figure 7.5. GESIFLOG for optimal control model

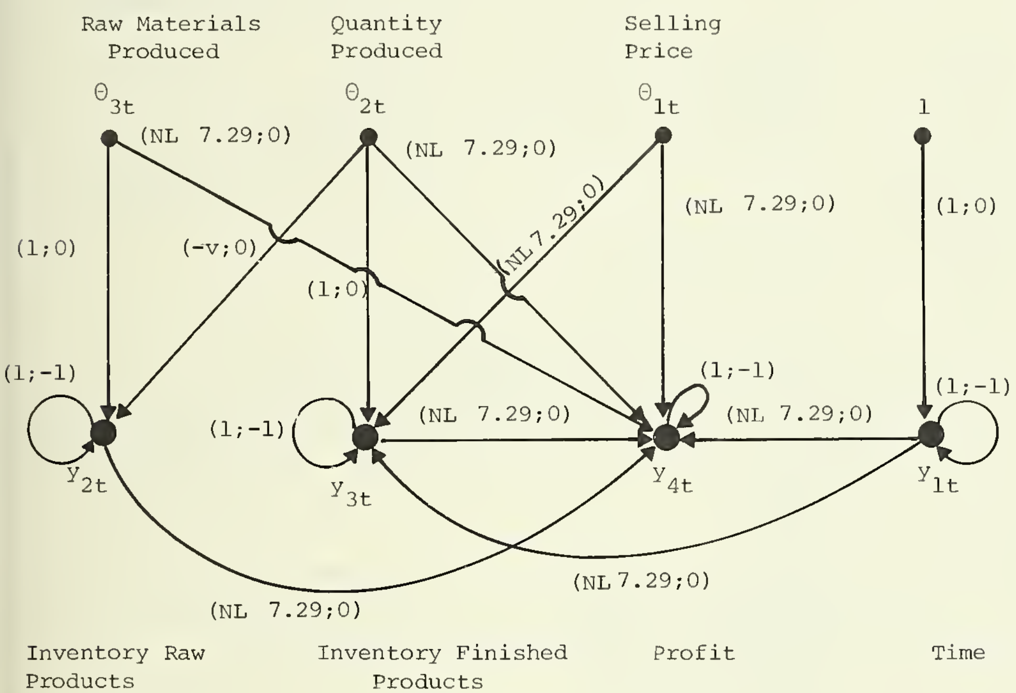


Figure 7.6 supplies the symbols explanations and numerical values for the basic optimization model:

Figure 7.6. Symbols, explanations and data for optimal control model

t	stage variable	$t = [1, n]$	
n	planning horizon	4	
y_{1t}, z_{1t}	time and its costate variable	$y_{10} = 0$ $y_{1n} = n$	
y_{2t}, z_{2t}	inventory raw products with costate variable	$y_{20} = 1$	
y_{3t}, z_{3t}	inventory finished products with costate variables	$y_{30} = 0$	
y_{4t}, z_{4t}	profit and its costate variable	$y_{40} = 0$	
Θ_{1t}	selling price		
Θ_{2t}	quantity produced		
Θ_{3t}	purchased quantity of raw products		
$S\ (y_{1t}, \Theta_{1t})$	dynamic price-demand function, e.g. generalized logistic function		
v	raw product - finished product explosion factor	1.5	
d	discount rate per period	0.1	
i	inventory cost of unit finished or raw product per period	5.0	
r	repulsion or SUMT parameter for raw and finished products	1.0	
s	depreciation factor for equipment	0.1	
C_W	factor wage function	50.0	
C_R	factor raw material price	10.0	
C_M	factor auxiliary material	20.0	
g	factor raw material cost	0.2	
ℓ	factor auxiliary material cost	2.5	
	expected values and variances		
α, var (α)	constant factor demand curve	3.0	$9.0 . 10^{-4}$
β, var (β)	time coefficient demand curve	-1.5	$2.25 - 10^{-4}$
γ, var (γ)	price coefficient demand curve	0.1	10^{-6}
S_∞, var (S_∞)	saturation level demand curve	500	25.

The model is described by the following equations (viz. Figure 7.5):

Time

(7.25) $$y_{1t} = y_{1(t-1)} + 1$$

Raw Products Inventory Level

(7.26) $$y_{2t} = y_{2(t-1)} + \Theta_{3t} - v.\Theta_{2t}$$

Finished Products Inventory Level

(7.27) $$y_{3t} = y_{3(t-1)} + \Theta_{2t} - S\ (y_{1t}, \Theta_{1t}), \text{ where}$$

(7.28) $$S(y_{1t}, \Theta_{1t}) = \frac{S_\infty}{1 + \exp\ (\alpha + \beta.\ y_{1t} + \gamma.\ \Theta_{1t})}$$

denotes a generalized logistic price-demand curve. Its parameters are explained in Figure 7.6.

Profits

(7.29) $$y_{4t} = y_{4(t-1)} + \frac{1}{(1+d)^{y_{1(t-1)}}} \cdot \{\Theta_{1t} \cdot S\ (y_{1t}, \Theta_{1t}) -$$

$$-i \cdot (y_{2t} + y_{3t}) - r \cdot (y_{2t}^{-1} + y_{3t}^{-1}) -$$

$$- \Theta_{3t} \cdot Rk_t - \Theta_{2t} \cdot Pk_t\}$$

The parameters in eq. (7.29) are again explained in Figure 7.6; Rk_t denotes raw material costs that increase with a linear time trend according to

(7.30) $$Rk_t = C_R + g \cdot y_{1t}$$

Pk_t denotes production costs

(7.31) $$Pk_t = C_W + C_M - \ell.\ y_{1t} - s\ .$$

As one can see the depreciation factor s is linked to the quantity produced Θ_{2t}. The underlying hypothesis for the value of the equipment.

(7.32) $v_t \geq 0$ is

$$v_t = v_{t-1} - s\ \Theta_{2t}, \text{ where}$$

$$s = \frac{v_0 - v_\infty}{Q_\infty}$$

v_0 denotes the initial value, v the residual value of the equipment, Q is an estimate of the total quantity one can produce over the lifetime of the equipment.

The objective of the model is to maximize total profits y_{4n} over a horizon of $n = 4$ periods. In eq. (7.29) total profits are described as profits accumulated in periods [0, 1, 2 . . . t-1], $y_{4(t-1)}$, and additional profits in period t. Profits are due to the difference between sales by value and proportional inventory costs for raw and finished products, raw material costs, production costs and hyperbolic penalty costs for too small inventories. The latter correspond to SUMT penalty costs as they were used by Fiacco and McCormick with non-linear programming problems [22, 59]. They are used to guarantee that the constraints $y_{2t}, y_{3t} \geq 0$ are never violated. Apart from this introduction, no explicit use of the SUMT technique has been made. Similar penalties could be introduced for the decision variables to guarantee $\Theta_{1t}, \Theta_{2t}, \Theta_{3t} \geq 0$. However, it will be seen that these restrictions are never active in the present example, so they have been omitted. The penalty function approach should become important whenever there is a more complicated objective function or more restrictions on endogenous state and decision variables to consider. Clearly, it complicates the linearization of a problem as is done whenever gradient methods are applied (e.g. Abadie [1]). But at present, the trade-off between unconstrained optimization methods using auxiliary or penalty functions and constrained optimization using approximation methods is difficult to determine.

It should be noted that sales by value in the model are described by a non-concave, but unimodal function of the decision variable Θ_{1t}. The optimal control problem expressed by eqns. (7.25 - 7.29) may also be interpreted as an optimization problem for y_{4n} under the equality restrictions eqns. (7.25 - 7.27). A number of authors have derived necessary and sufficient conditions for optimality for such problems (viz. Katz [98], Fan, Wang [57], Wilde, Beightler [162]. Notably, Holmes [88] and Benavie, Gould [12] have shown how they could be derived from the Kuhn-Tucker conditions for non-linear programming. For non-concave objective functions and non-linear constraints they are not in general applicable.

Many parameters of such models as expressed by eqns (7.25 - 7.32) are subject to error under practical circumstances. This is especially the case whenever the interactions of the firm with its environment are described. Examples are the demand and cost functions of the model as they are in

practice determined by estimation from non-experimental data. In the example, the generalized logistic price-demand curve is represented by a stochastic equation.

Using expected values or certainty equivalents of the parameters in a deterministic solution of the problem, as has been done by several authors with similar models (viz. Simon [142], Krouse [104]), would have two main disadvantages: First, one could not take explicit account of risk. Secondly, as many authors, notably Howrey and Kelejian [91], have shown, except for linear systems, the expected results derived with expected parameters will in general differ systematically from expected results obtained using parameter distributions. Sensitivity or post-optimal analysis would for these cases frequently lead to fallacious results due to the fact that one could not take into account all the interaction effects of variables and parameters. Therefore, an evaluation of the stochastic problem is preferable. However, serious problem often arise either due to computational difficulties or the fact that a certain solution technique is not appropriate for discrete non-linear and stochastic problems. Often, the first difficulty, i.e. storage requirements and solution time, would be encountered when stochastic dynamic programming [130] is used, the second difficulty could arise from the fact that at present, some non-classical variational methods which are based on Pontrjagin's maximum principle have only been used for very special discrete and continuous stochastic problems [107, 149, 16]. Kushner and Schweppes [107, p. 297] give some necessary conditions for an optimum of discrete stochastic systems which for eqs. (7.27) and (7.29) are not fulfilled. Chow has discussed a linearization of the problem [35, 36].

In the sequel it will be shown that some of these difficulties may be overcome if one derives an optimal stochastic solution empirically using the discrete and deterministic maximum principle together with a Monte Carlo simulation of the deterministic solution. More explicit economic interpretations of the maximum principle have been given by Dorfman [52], Benavie [13], Intriligator [93, pp. 292-369] and Arrow and Kurz [6].

Using the maximum principle to optimize the above model, one introduces the so called Hamiltonian

(7.33) $$H_t = \Sigma_i\, z_{it} \cdot y_i\, (y_{j(t-1)}, \Theta_{kt}) \text{ with}$$
$$k = 1, 2, 3, ; j = [1, 4] ; i = [1, 4].$$

The costate variables z_{it} serve a similar purpose as the Lagrange multiplier in classical optimization problems under equality constraints. One

can show that they have to obey the so called Hamilton-Jacobi differential equations

$$z_{it(t-1)} = \frac{\partial H_t}{\partial y_{i(t-1)}} \tag{7.34}$$

One sees immediately that the eqns. (7.25 - 7.29) may be represented by

$$y_{it} = \frac{\partial H_t}{\partial z_{it}} \tag{7.35}$$

Taking these - for the problem - eight difference equations of the first order into consideration, the maximum principle states as a necessary condition for the maximization of accumulated and discounted profits, y_{4n}, that the maximum of the Hamiltonian eq. (7.33) be saught for all periods or stages with respect to the decision variables Θ_{1t}, Θ_{2t}, Θ_{3t} for fixed $y_{i(t-1)}$ and z_{it}, i.e.

$$H_{tmax} = \max_{\Theta_{1t},\, \Theta_{2t},\, \Theta_{3t}} H_t\,(z_{it}, y_{it}, \Theta_{kt}). \tag{7.36}$$

In addition, the costate variables have to fulfill the following end conditions

$$z_{2n} = z_{3n} = 0 \;;\quad z_{4n} = 1 \tag{7.37}$$

whereas z_{1n}, the costate variable for the time variable y_{1n} and t = n may attain arbitrary values.

For the present example one has

$$\frac{\partial H_t}{\partial \Theta_{jt}} = 0,\ j = [1, 3], \tag{7.38}$$

and for the (1x1), (2x2) and (3x3) determinants of second derivatives D_j

$$D_j = \det\left(\frac{\partial^2\ (-H_t)}{\partial\Theta_{jt}\ .\partial\Theta_{it}}\right) > 0 \quad i = 1, 2..\ j \tag{7.39}$$

as necessary and sufficient conditions for a maximum of the Hamiltonian.

Eq. (7.38) gives three further equations for the costate variables z_{it}, i = 2, 3 and by suitable substitutions of eqns. (7.34 - 7.35) and the initial and end values of the y_{it} , i = [1, 4], and the end values eq. (7.37), one obtains the optimal values of the decision variables from a solution of the system eq. (7.40 - 7.44):

$$\Theta_{1t} = Pk_t + v.\ Rk_t - S_t \cdot \left(\frac{\partial S_t}{\partial \Theta_{1t}}\right)^{-1} \quad t = [1, n] \tag{7.40}$$

$$\Theta_{2t} = S_t - y_{3(t-1)} + \sqrt{\frac{d}{i + (z_{3(t-1)} - z_{3t}) \cdot (1+d)^{y_{1(t-1)}}}}, \quad t + [1, (n-1)] \tag{7.41}$$

$$\Theta_{3t} = v \cdot \Theta_{2t} - y_{2(t-1)} + \sqrt{\frac{d}{1 + (z_{2(t-1)} - z_{2t} \cdot (1+d)^{y_{1(t-1)}}}}, \quad t + [1, (n-1)] \tag{7.42}$$

$$\Theta_{2t} = S_n - y_{3(n-1)} + \sqrt{\frac{d}{i + Pk_t + v \cdot Rk_t}} \tag{7.43}$$

$$\Theta_{3t} = v.\Theta_{2n} - y_{2(n-1)} + \sqrt{\frac{d}{i + Rk_n}} \tag{7.44}$$

The non-linear equation (7.40) was solved by a fast version of the Regula Falsi. The result, i.e. S_t, was substituted into the equations defining Θ_{2t}, Θ_{3t} and with the numerical values given in Figure 7.6 resulted in the optimal deterministic solution exhibited in Figure 7.7.

Figure 7.7: Optimal solution of deterministic control problem

t	Θ_1	Θ_2	Θ_3	y_{4t}
1	90.02	1.29	1.35	- 20.38
2	90.04	4.49	6.73	- 10.41
3	90.30	19.03	28.55	+ 53.94
4	91.43	68.16	102.07	+338.86

As one can see, the maximum profit that one may obtain for the four period example is approximately y_{4n} (max) $\tilde{-}339$ (monetary units).

It has been mentioned before that in practice price-demand and cost functions will either be supplied subjectively or have to be estimated by econometric methods. In fact, chapter 6 indicated a number of techniques that are available for this purpose.

It is not at all difficult to perform a Monte-Carlo simulation of the deterministic solution described above. Under the usual assumptions, the parameters possess a multivariate normal distribution and may readily be simulated by available subroutines (e.g. [121, pp. 297-398]), once an estimate of the variance-covariance matrix is given.

If for example one is interested in an estimate of the expected value of aggregated discounted profits y_{4n}, then an estimate of the mean follows

from

$$\bar{y}_{4n} = \frac{1}{m} \cdot \sum_{i=1}^{m} y_{4n}^{(i)} \tag{7.45}$$

and the sample variance may be determined from

$$\bar{\sigma}^2 = \frac{1}{m-1} \sum_{i=1}^{m} (y_{4n}^{(i)} - \bar{y}_{4n})^2 \ . \tag{7.46}$$

The constant m denotes the number of replications and $y_{4n}^{(i)}$ the result of one individual simulation. Confidence limits for the expected value follows for small m for

$$y_{4n} = \bar{y}_{4n} \pm t_{\alpha(m-1)} \cdot \frac{\bar{\sigma}}{\sqrt{m}} , \tag{7.47}$$

where $t_{\alpha(m-1)}$ is the value of the Student t-distribution at probability level α with (m-1) degrees of freedom (viz. e.g. Kleijnen [101]).

For the sales-production inventory example described, m = 492 replications of the deterministic solution were necessary to obtain $\bar{y}_{4n}$ accurately at the 0.01 level. The results of these experiments are shown in Figure 7.8.

Figure 7.8: Optimal solution of stochastic control problem

t	Θ_1	Θ_2	Θ_4	y_{4t}
1	90.03	1.30	1.37	-20.31
2	90.05	4.53	6.79	-10.07
3	90.31	19.17	28.75	55.27
4	91.46	68.35	102.36	342.85

As to be expected, there is a significant difference between the deterministic and the stochastic solution. It is quite small for the example chosen, but this only results from the simplicity of the model and the small variances of the parameters given in Figure 7.6.

The great number of experiments necessary to determine $\bar{y}_{4n}$ with sufficient accuracy certainly speaks against the simulation approach.

However, very often a user is likely to possess some qualitative a prior knowledge about the response of his objective function to changes in the system's random elements. For instance from eq. (7.28), it is to be expected that profits increase with increasing demand saturation level S_∞ or decrease with increasing price coefficient γ. This qualitative information-even if the effects had the opposite trend - may be used to design much

more efficient simulation experiments using such techniques as stratified, antithetic variate, importance or regression sampling (viz. Hammersley, Morton [72], Moy [119, pp. 269-289], Kleijnen [101]). Two such techniques - regression and antithetic variate sampling - have been used with the model described [134]. It was possible to obtain the expected value $\bar{y}_{4n}$ of discounted accumulated profits for $\alpha = 0.01$ already with $m \approx 48$ replications of the optimal deterministic solution as compared to $m = 492$ for the original experiment. If one considers that the determination of the stochastic solution only took approximately 7 sec. of CPU-time and nearly negligible storage on an IBM 370/155, one can imagine a variety of circumstances where this trade-off between computing costs versus solution accuracy and additional information (i.e. variance of $\bar{y}_{4n}$) is acceptable.

Three further points are worth mentioning in connection with the model described. They deal with the solution technique chosen, the problem of multiple objectives and the integration of the optimization submodel into a corporate model.

First, it should not be concluded that the discrete maximum principle is always as simple to apply as in the example given. It may not be at all applicable if several continuity, differentiability and convexity conditions are not fulfilled. Equations (7.34 - 7.35) express differentiations which are assumed to exist. Furthermore, the maximization of the Hamiltonian eq. (7.36) may not be as simple as indicated by eqns. (7.38 - 7.39). If there exist inequality restrictions on the decision and endogenous state variables or if variables are only discretely defined, all the optimization and searching techniques mentioned in previous chapters become involved. Frequently, one would have to use mathematical programming techniques to optimize H_t separately under constraints for all periods $t=[1,n]$. Since these solutions would only in exceptional cases lead to the boundary conditions for the costate variables specified by eq. (7.37) or similar boundary conditions for the endogenous variables y_{it}, $i = [1,4]$, searching or other root seeking methods would become involved. The Hooke-Jeeves method has been found to be a pragmatic method to solve this kind of problem.

Second, the problem of multiple objectives or responses may be encountered in optimal control problems as in all the more static problems which have previously been discussed. In fact, the model described is well suited to illustrate this point. The profit function eq. (7.29) includes a penalty term $r \cdot (y_{2t}^{-1} + y_{3t}^{-1})$ which has prevented negative inventory levels from appearing in the optimum solution. In practice, the penalty constant r and

the functional form of the penalty term will be assessed subjectively. Similar terms would appear in the objective function whenever penalties are associated with deviations from targets or aspiration levels. The utility trade-off between the penalty terms and other goals described in the objective function would have to be determined if one is not dealing with non-commensurable goals and preemtive weights. In practice, it has to be determined, whether the inaccuracy of goal weights does not offset the value of the optimization.

Third, the model described should not create the impression that optimal control techniques will become very important in practical corporate modeling applications in the near future. On the contrary, the discussion of optimization methods in corporate modeling clearly indicated that optimizing and also "What to do to achieve?" investigations are restricted to very special model structures. There is no question that "What if?" experiments require minimal assumptions and that also in the near future optimizing and "What to do to achieve?" type investigations will have to be combined with the former.

Under these circumstances, it is very important that the corporate modeling system used easily allows the inclusion and deletion of optimizing submodels from the corporate model. This will only be possible if the system possesses a modular structure. The CIBA-GEIGY corporate simulation and modeling system COMOS for example, possesses a number of macro-statements to achieve this task. So the goal programming example given in Figure 7.2 and 7.3 has been generated using only COMOS statements. In chapter 8, another example will be given. A number of other systems available do not possess such statements, but allow the integration of optimization submodels over an interface generated by a higher level problem oriented programming language such as FORTRAN IV or PL/I. Figures 7.9 and 7.10 represent examples for the integration of the optimal control model described into a budgeting model. The basic budgeting model has been programmed in a combination of IBM's PSG (Programs Systems-Generator, viz. Lande et al. [109]) and FORTRAN IV. An initial model solution of the budgeting model has been shown in chapter 2, Figures 2.8 and 2.9. The optimal control model has been programmed in FORTRAN IV and the link between the optimization model and the PSG budgeting model was also established by FORTRAN statements. The values of the optimal stochastic solution of the control problem given in Figure 7.8 may not be seen directly from Figures 7.9 and 7.10 because other equations, not contained in the optimization model, have also been evalu-

Figure 7.9. Balance with investment and stochastic optimization financial corporate model

FINANCIAL STATEMENT — Company Australia

5-Year-Plan 1977 to 1981

Conversion rate into SFR.	4.80	4.80	4.80	4.80	4.80	4.80	4.80	4.80
				Plan				
	1974	1975	1976	1977	1978	1979	1980	1981
Assets								
Liquid Funds								
Receivables	1292	1694	2101	2606	3232	4008	4971	6166
Inventories	4684	5429	7135	9318	11505	13678	15851	18010
Other Current Assets	100	100	150	150	150	150	150	150
Total Current Assets	6076	7223	9386	12074	14887	17836	20972	24325
Fixed Assets	975	960	1273	1733	1978	2263	2593	2974
Other Fixed Assets	2	2	2	2	2	2	2	2
Total Long Term Assets	977	962	1275	1735	1980	2265	2595	2976
Total Assets	7053	8185	10661	13809	16866	20100	23567	27301
Banks	2012	2324	2244	2239	2212	2153	2024	1585
Current Account Parent Comapny	1800	2000	2300	2645	3042	3498	4023	4626
Other Short Term Liabilities	600	740	890	1070	1287	1548	1862	2240
Total Current Liabilities	4412	5064	5434	5954	6542	7199	7909	8451
Parent Company Loans	729	729	729	829	829	829	829	829
Banks & Other Financial Establishments	1862	1862	1862	1962	1952	1942	1932	1922
Other Long Term Liabilities	863	963	963	1013	1008	1003	998	993
Total Long Term Liabilities	3454	3554	3554	3804	3789	3774	3759	3744
Share Capital	2000	3000	3500	4800	6100	7400	8700	10000
Reserves	134	134	134	134	134	134	134	134
Retained Earnings	-2947	-3567	-1961	-883	302	1593	3065	4972
Total Liabilities	7053	8185	10661	13809	16866	20100	23567	27301
Local Profit after Taxes	1742	-620	1606	1078	1185	1292	1472	1907
Increase/Decrease	1742	-620	1606	1078	1185	1292	1472	1907
Total Bank Credit Lines	1686	1686	2000	3000	3000	3000	3000	3000

Figure 7.10. Profit and loss statement with investment and stochastic optimization financial corporate model

PROFIT AND LOSS STATEMENT — Company Australia

5-Year-Plan 1977 to 1980

Conversion rate into SFR.	4.80	4.80	4.80	4.80	4.80	4.80	4.80	4.80
				Plan				
	1974	1975	1976	1977	1978	1979	1980	1981
Sales								
- Third Parties	10374	12670	14604	17519	21108	25607	31887	42169
- Intercompany								
Total Sales - Local Currency	10374	12670	14604	17519	21108	25607	31887	42169
- SFR.	49795	60816	70099	84090	101317	122916	153057	202413
Division Expenses	1185	1633	2106	3559	5818	9652	16020	26598
Total Local Cost of Goods Sold	7579	8434	10705	13588	17348	22276	29348	40780
Division Local Contributions	1610	2603	1793	372	-2058	-6321	-13482	-25209
Function Expenses								
Finance	638	705	780	863	955	1056	1169	1293
Personnel	74	91	195	418	895	1919	4112	8810
Managerial	169	165	190	205	220	237	256	276
Loss on Revaluation								
Other Income and Expenses								
Total Function Expenese	881	961	1165	1486	2071	3213	5536	10379
Local Contribution	729	1642	628	-1113	-4128	-9533	-19018	-35588
- Expenses	350	370	375	380	385	390	396	401
- Income	1363	-1892	1353	2571	5699	11215	20885	37896
Income From Minority Interests								
Local Profit Before Taxes	1742	-620	1606	1078	1185	1292	1472	1907
Taxes								
Local Profit After Taxes	1742	-620	1606	1078	1185	1292	1472	1907
Payments to Minority Share Holders								
Local CIBA-GEIGY Net Profit	1742	-620	1606	1078	1185	1292	1472	1907

ated. The four period optimization model deals with the time period from 1978 to 1981 only. This may be seen from line number one of Figure 7.10: Sales to third parties differ from the initial solution only beginning with the year 1978. It has been assumed that the sales-production-inventory system was started up in 1977 with an investment in fixed assets of 250 (monetary units). This may be seen from line six in Figure 7.9. The investment was financed by a loan from the parent company of 100 (m.u.), a long term bank credit of 100 (m.u.) and a credit of third parties (other long term liabilities) of 50 (m.u.). For the last two credits the firm has, starting in 1977, to pay 8% interest which is booked on short term crėdits, since the daughter company does not keep liquid funds (viz. line one of Figure 7.7). Starting in 1978, the firm has to pay back 10% of the bank credits per year, whereas parent company loans are neither paid back, nor is there any interest to pay on them. The installment of the new investments costs 50 (m.u.) in 1977 and raw materials have been purchased in 1977 for 10 (m.u.) to be able to start the production in 1978 and thereby to attain the initial inventory level for raw products $y_{20} = 1$ specified in Figure 7.6. Appropriate bookings have been made on divisional expenses, short term bank credits and inventories. Similar bookkeeping equations effect the distribution of costs and sales of the operating sales-production-inventory system on the appropriate accounts in the balance and income statement. Since inventory penalty costs contained in eq. (7.29) have the character of opportunity costs for the optimization model only, they do not appear in the financial statements.

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FOOTNOTES TO CHAPTER 7

1. New variable costs and expenses are expressed as a fixed proportion (old values) of new sales.

2. Parts of this chapter are based on F. Rosenkranz "Deterministic Solution and Stochastic Simulation of a Simple Production Inventory Model Zeitschrift für Operations Research 17, 1973, pp. B 141-152 [134].

Corporate Simulation and Planning Systems

CRITERIA FOR THE EVALUATION OF CORPORATE SIMULATION AND PLANNING SYSTEM [1]

In previous chapters, corporate model building activities have been described as a stepwise construction process incorporating the steps of

1. specification of objectives,
2. investigation, collection and prepration of data,
3. formulation of equations,
4. coding for a computer,
5. estimation and solution,
6. testing, verification, and validation,
7. implementation and use as an experimental tool.

With the exception of the first step all these steps may be supported by computer software. In this chapter, CSPSs which have been developed for this purpose will be described in more detail.

In general, a CSPS consists of something like a language supervisor program which is coded in a general purpose or assembler language. It controls a number of ready made building blocks which allow access to a model's database and which perform user defined calculations with ready made methods using sometimes ready made submodels.

Empirical investigations on the distribution of effort over different modeling activities for management science models in general [21], corporate models in particular [23] show that the greatest percentage is spent on the first two modeling steps. Notably, the collection, preparation, and selection of model data, the preparation of output forms and the construction of a model's database is a time and money consuming job. A CSPS with its standardized commands should be able to support these activities more

efficiently than a higher-level problem-oriented language. The same one would expect for the other modeling steps, especially if the user of the model participates directly in the modeling process and does not possess a special knowledge of data processing. Ideally statements, commands, and routines of a CSPS allow a faster, more flexible and transparent coding of a model, thus reducing the costs of programming, testing, documenting, and changing.

When evaluating a CSPS, it is advisable to compare the facilities it offers, first, with the requirements that follow from the steps of the model design procedure and, second, with the facilities offered by other systems. Some points which might be of interest for such a comparison are given below.

1. Main Application Area
   - Corporate Modeling
   - Financial Modeling
   - Marketing Modeling
   - Production Modeling
2. Type of System
   - Fixed Structure
   - Flexible, Modular Structure
3. Hardware Requirements
   - Main Storage
   - External Storage
   - Input-Output Facilities
4. Software Requirements
   - Compilers and Source Languages
   - Interfaces
   - File Organization, Data Access Methods
5. Mode of Operation
   - Batch
   - Real Time
   - In-house
   - Service bureau
6. Costs of System
   - Purchasing, Leasing
   - Consulting, Training
   - Storage
   - Operation

7. Type of Language
   - Free Format-Fixed Format
   - Compiler-Interpreter
   - Restrictions
   - English Like or Symbolic Text
8. Flexibility of Input and Output
   - Choice and Number of Formats
   - Sequence
   - Graphics and Histogramms
9. Type of Database
   - File and Data Set Structure
   - Internal, External Database
   - Connection and Hierarchies of Databases and Files
10. Basic Time Intervals
    - Maximum Number
    - Specific Periods
    - Interval Transformations
11. Maximum Size of Model
    - Statements
    - Number and Size of
      - Arrays
      - Matrices and Tables
      - Files and Number of Data, Variables/File
12. Arithmetic
    - Operators
    - Column Arithmetic
    - Line Arithmetic
    - Table Arithmetic
    - Built-in Functions
13. Systems Logic
    - Linear Sequential
    - Logical Branching
    - Index Calculations
    - IF, GOTO
    - DO Loop, END
    - Forward, Backward Iterations
    - Labels

- Subroutines
- Table Access Methods

14. Handling of Non-Numeric Data
    - Character String Operations
    - List and Tree Processing
    - Set Statements
15. Macro-Instructions
    - Practitioner Methods
        - Interpolation, Extrapolation
        - Financial Indicators
    - Short Term Forecasting
    - Trend Forecasting
    - Econometric Methods
    - Specification and Verification Testing
    - Random Numbers and Stochastic Simulation
    - Matrix Algebra and Linear Programming
    - Nonlinear Solution and Optimization Methods
    - Sensitivity Analysis
    - Experimental Designs
    - Graph-Analysis
16. Security System
    - Physical Security of Database, Models and CSPS
    - Authorization Codes and Passwords for Database, Files, Models and CSPS - Privacy
17. Documentation and Support
    - Users and Systems Manuals
    - Debugging and Error Tracing
    - Menu Programs, Prompting and 'Help' Explanations
    - Computer Aided Instruction
    - Consulting Support

The market for CSPSs is a highly competitive one and a company which starts corporate model building may in principle access and choose among in the order of thirty to fifty different packages and systems. A check-list like the one given in the previous section may be used for the evaluation of alternative CSPSs after the objectives and the nature of a corporate modeling project have been defined.

It is not within the scope of this chapter to give a systematic and exhaustive description and comparison of all CSPSs. However, in the following pages, some systems which are frequently employed will briefly be described, before a more explicit description of the CIBA-GEIGY COMOS is presented.

DESCRIPTION OF SOME SELECTED SYSTEMS

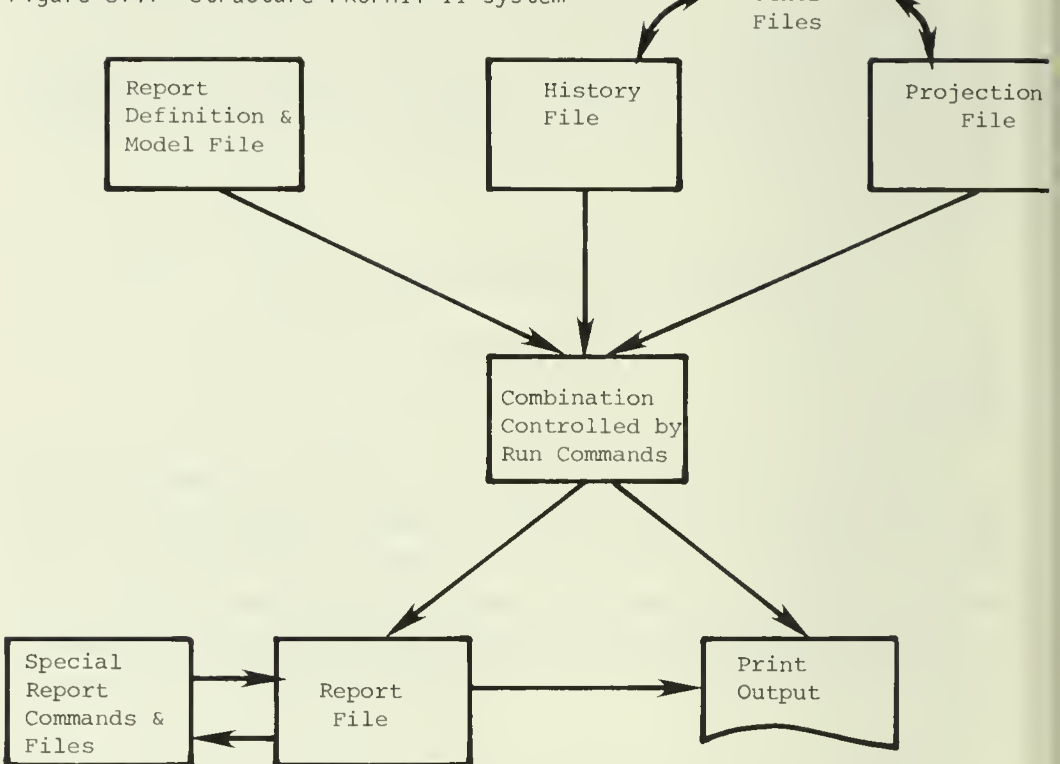
PROPHIT II

PROPHIT II is a reporting, planning and budgeting system developed by Control Data Corporation which operates mainly in interactive mode. PROPHIT II was created already in 1970. As a consequence, its concepts and modeling facilities are not as far developed as with some of the systems which have been developed more recently. However, the system is widely used and interfaces to other subsystems permit a variety of modeling applications.

PROPHIT II commands and data are stored on different files (viz. Figure 8.1). The report definition or model file contains commands which specify the model structure and reports which are to be stored or printed out. The history file contains historic model data and additional report specifications, whereas the projection file holds projected or future values of model variables or specifications of projection methods for model variables. The execution or run phase of a PROPHIT II program is controlled by specific run commands. The results are written on the report file or printed out. Special report commands and additional files are employed to perform further experiments and evaluations of a modeling result.

PROPHIT II does not possess any interlanguage communication facilities. Communication with other systems has to be achieved using common files or file interfaces. PROPHIT II can be linked to database management systems and modeling packages. PROPHIT II may be combined with STATPACK for statistical evaluations, the TIMEPACK subsystem may be employed for time series analysis, econometric modeling and forecasting. The system itself is mainly designed to evaluate smaller numbers of financial relations and identities. Neither the commands nor the available built-in functions of the system allow an integrated support of marketing and production sub-

Figure 8.1. Structure PROPHIT II system



models. The system is characterized as "computerized columnar spread sheet" [11].

PROPHIT II variables are defined as numeric line variables. In the model specification phase, their names and characteristics are stored on the model file, whereas the data are obtained from the history and projection files. Figure 8.2 gives an impression of the combination of variable information. Systems developed more recently usually employ only one file to store the information shown in Figure 8.2.

Figure 8.2. Arrangement of PROPHIT II information

Model File	History File	Projection File
Sales		
Costs	Historical	Future
Profits	Data	Date

PROPHIT II commands are basically line oriented. This is true for all the three input files mentioned. Data are entered linewise for the history and projection files. Column manipulations must in most cases be specified using a special report command 'COLUMN' together with a special column file. The lines are identified by line numbers, not by English-like identifiers. All calculations are performed in a two dimensional calculation matrix whose maximum size is restricted.

In contrast to later developed systems PROPHIT II does not incorporate an elaborate CSPL. Its commands are based on a code system which is employed to specify line operations. Figure 8.3 shows the general format and an example for commands specified for the report definition or model file.

Figure 8.3. Format of command on model file

Line Number	Line Title	Operation Code	Print Code	Totaling Code	Particular values, factors line/column references

1Ø	NET_SALES,	4Ø,	1,	1		
2Ø	COST_OF_SALES	4Ø,	1,	1		
3Ø	GROSS_PROFIT	7 ,	1,	1,	1Ø,	2Ø

A model consisting of three "statements" is shown. Variable NET_SALES is contained in line ten of the calculation matrix, code 4Ø specifies that it is read from the history and projection files. It is printed out (print code '1') and a line total is written into a totaling column (totaling code '1'). The same is done for variable COST_OF_SALES which is contained in line twenty of the calculation matrix. Variable GROSS_PROFIT is obtained by a subtraction of line twenty from line ten (operation code 7). Again, a total is calculated and printed.

The operation codes used for the model file may be subdivided into codes which

- load data from other files
- specify printing and spacing operations
- summing operations
- arithmetic calculations
- specific numeric and logical operations, such as data carry forward operations, e.g. needed to calculate variables of a balance, logical operations to switch calculations between several lines depending on the result of a comparison operation. Other codes

effect a shift of data across a line by a specified number of columns and thus allow the construction of loops or repetitive data evaluations.

A different code system is used to define the extrapolation of line variables for the projection file. The practitioner methods described in chapter 6 are available, in addition polynomial trends may be specified. In total the number of 'built-in functions' offered by the PROPHIT II system is very restricted. A great disadvantage of the system for corporate modeling applications is that it does not distinguish or allow for indexed variables and index calculations. The repetitive evaluation of commands and a logical branching is difficult to specify compared to later systems.

The execution of PROPHIT II commands on the three input files and the generation of the report file and printing of model output is controlled by run commands. They also control the creation and deletion of files and support the error debugging ('CHECK' command) and documentation of a PROPHIT II program ('ILLUSTRATE' command). Special report commands may be used to manipulate model data which are stored on the report file. Some of them require the creation of additional files. Examples are the 'WHAT IF' command which allows the recalculation of a report after some changes have been specified on a 'WHAT IF' file, the 'CONSOLIDATE' command which allows the calculation of a report from several report files. A 'VARIANCE' command controls a deviation analysis between different model solutions stored on report files.

CALL/AS

"Application system (AS) is an integrated information-handling system offering facilities for data creation, management and presentation" [30]. It has been developed by IBM/UK and is available on the IBM time-sharing network. It incorporates many facilities and commands which have already been described for PROPHIT II. Conceptually, it builds on earlier IBM developments like PSG [25] and STRATPLN [28]. Like PROPHIT II, AS is mainly suited for the construction of "ad hoc" or "throw away" interactive financial corporate models. It comprises only few and simple commands and statements and may easily be taught to planners who are not data processing oriented.

Compared to PROPHIT II, several simplifications and generalizations of the database, the reporting and modeling facilities may be noticed. AS

again works with lines of a calculation matrix which is stored on an external file. Except from variable identifiers which form the head of a data record only numeric data are dealt with. Similar to PROPHIT II, variables are addressed by line numbers. But the modeling code system has been replaced by a free format interpretative modeling language. The statement

```
2030   LET NET_CASH = CASH_IN - CASH_OUT
```

gives an example. It applies to complete lines of the calculation matrix and substitutes a DO-loop of a problem oriented language like FORTRAN or PL/1.

The artificial distinction between PROPHIT II report definition and model files as well as history and projection files is not maintained.

An AS translater transforms AS language statements into a code which is stored on disk during the model specifications phase. This code is sequentially executed during the solution phase of a model. AS does not allow for systems of simultaneous model equations. A simultaneity is recognized as an error and may only be circumvented by programming an iterative solution employing initial values and AS "IF" and "DO" statements. Recursive equations are automatically sequenced. Logical branching and a repetitive evaluation of a group of statements is possible as may be seen from the self-explanatory inventory example shown below:

Figure 8.4: AS-Program

```
10   OPENING_STOCK = 1000 & IF (@PER >1) = CARRY
                       (CLOSING_STOCK)
20   RECEIPTS = 500
30   ISSUES = 300 + PERIOD (50)
40   CLOSING_STOCK = OPENING_STOCK + RECEIPTS - ISSUES
```

Using some report generator commands, the following result would have been obtained:

Figure 8.5: Results AS-Program

	JAN	FEB	MAR	APRIL
OPENING_STOCK	1000	1150	1250	1300
RECEIPTS	500	500	500	500
ISSUES	350	400	450	500
CLOSING_STOCK	1150	1250	1300	1300

The index @PER denotes columns of the data matrix. For the given example, it is increased automatically by one during every evaluation of the statements. The built-in function CARRY effects a carry-forward operation. It may be used to specify leads and lags in an AS model. This may more elegantly be expressed by the LAG built-in function as is shown in the following example.

```
1100  ACCOUNTS_RECEIVABLE = LAG
      (INCOME_FROM_GOODS_SOLD , -2) * 0.98
```

It specifies a lag of two for variable INCOME_FROM_GOODS_SOLD.

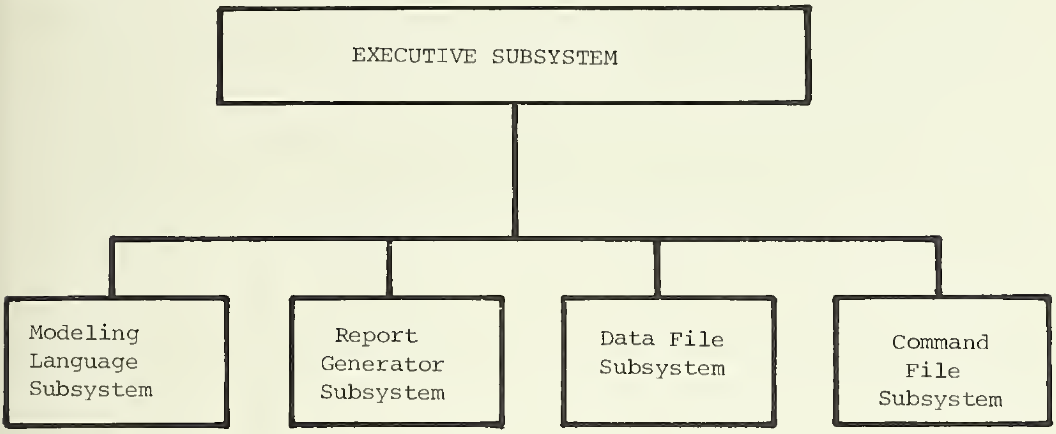
AS contains a number of further built-in functions. However, their number is rather restricted. Since it does not work with indexed variables and does not incorporate interlanguage communication facilities and subroutine calls, applications are mainly restricted to the evaluation of financial identities. Like with PROPHIT II statistical modeling and forecasting may be done using AS model files and separate AS subsystems, such as the AS Statistics or Forecasting systems. These contain multiple linear and stepwise regression estimation methods and restricted means for statistical verification testing and forecasting.

IFPS

IFPS is EXECUCOM's interactive financial planning system [17]. It too is a system to support the construction of ad hoc planning and budgeting models. In a record and table line oriented fashion, it mainly supports the formulation, evaluation and solution of financial identities and statements.

IFPS incorporates five subsystems as is shown in Figure 8.6

Figure 8.6. IFPS subsystems



The executive subsystem is used to call the other subsystems by EXECUTIVE commands. In addition, it contains commands to specify and consolidate data files, to list, delete, copy, combine and consolidate IFPS models and reports. The latter two commands are of sufficient flexibility to allow tree calculations and hierarchical modeling. Consolidations of models may be weighted as is shown below

CONSOLIDATE MODEL 1 (Ø.5) MODEL2 (Ø.3) MODEL3 (Ø.2)

The modeling language subsystem is used to create, edit, solve and print the results from IFPS models. Models consist of statements of the IFPS language. They are written, processed and stored in a linewise fashion. Variables appearing in a IFPS program refer to lines or records of a data file. Although the variables of a model and their values as a function of time define the lines and columns of a calculation matrix formed by line records, no use of matrix or vector methods is made. Single matrix elements may be addressed explicitly by specifying line and column indices. However, no index calculations and repetitive evaluation of IFPS statements may be specified by statements of the language (e.g. no GOTO- or DO-statements). Statements of the command file subsystem have to be used for the repetitive evaluation of an IFPS program. Logical branching capabilities are available by IF-THEN-ELSE statements. Special COLUMN statements may be used to specify calculations between columns of a data matrix. However, IFPS does not allow for column variables, but leads and lags for line variables may be specified.

The language possesses a number of macros, built-in-functions, and subroutines to perform frequently encountered modeling tasks. Examples are commands to perform totalling, built-in-functions to calculate specific functions (e.g. MAX, MIN, NATLOG), perform financial calculations (e.g. net present worth), simple descriptive forecasts, generate random numbers for a well developed risk analysis and subroutines to calculate depreciation schedules. One may call on user written FORTRAN functions and subroutines from an IFPS program.

The language subsystems incorporates commands to experiment with a model. The modeling steps of equation specification and solution are separated. The latter may be specified by a SOLVE command. IFPS incorporates algorithms for a sequencing of recursive equations, the iterative solution of simultaneous linear equations, as well as a procedure to determine goal-solutions. Several "What-if?" investigations of a model may be formulated using a specific "What-if?" command and statements of the language.

The IFPS report generator subsystem incorporates commands to specify, format, and print customized reports which cannot be written using statements of the modeling language subsystem.

The data file subsystem allows the creation, updating, deleting and editing of permanent IFPS data files. Data input and output is again linewise. The subsystem contains commands which effect the storage of alternative model solutions.

The command file subsystem operates with permanent files on which IFPS commands and directives may be stored. The execution of the stored commands may be initiated by other IFPS commands, thus reducing the effort needed to specify operations which use many commands. Specific command file control statements allow the alteration or interruption of the execution sequence of a command file. Control may be transferred to other statements stored on a Command File using the GOTO control statement. A COND control statement transfers control of a command file execution back to the user and the execution is continued conditional on his answer. This allows the construction of customized dialogues.

PLANCODE

PLANCODE is IBM's Planning, Control, and Decision Evaluation System and is available in two as yet not fully integrated subsystems PLANCODE/S and PLANCODE/I [30]. The former was especially designed for the construc-

tion of larger planning models which are operated in batch mode. The latter may be understood as an extension of earlier IBM developments such as STRATPLN and CALL/AS. PLANCODE/I is mainly conceived for the support of smaller ad hoc models, although rather powerful matrix statements permit the construction and experiments with larger models as well.

Compared to the systems described above, both PLANCODE/S and PLANCODE/I incorporate several important generalizations of the database structure and simulation language.

Like the other systems, PLANCODE still basically works with numeric data. However, constants or parameters, line data or variables and matrix data are distinguished. The database consists of tables which may have up to four dimensions for PLANCODE/S and up to three dimensions for PLANCODE/I. Figure 8.7 supplies an example for the former.

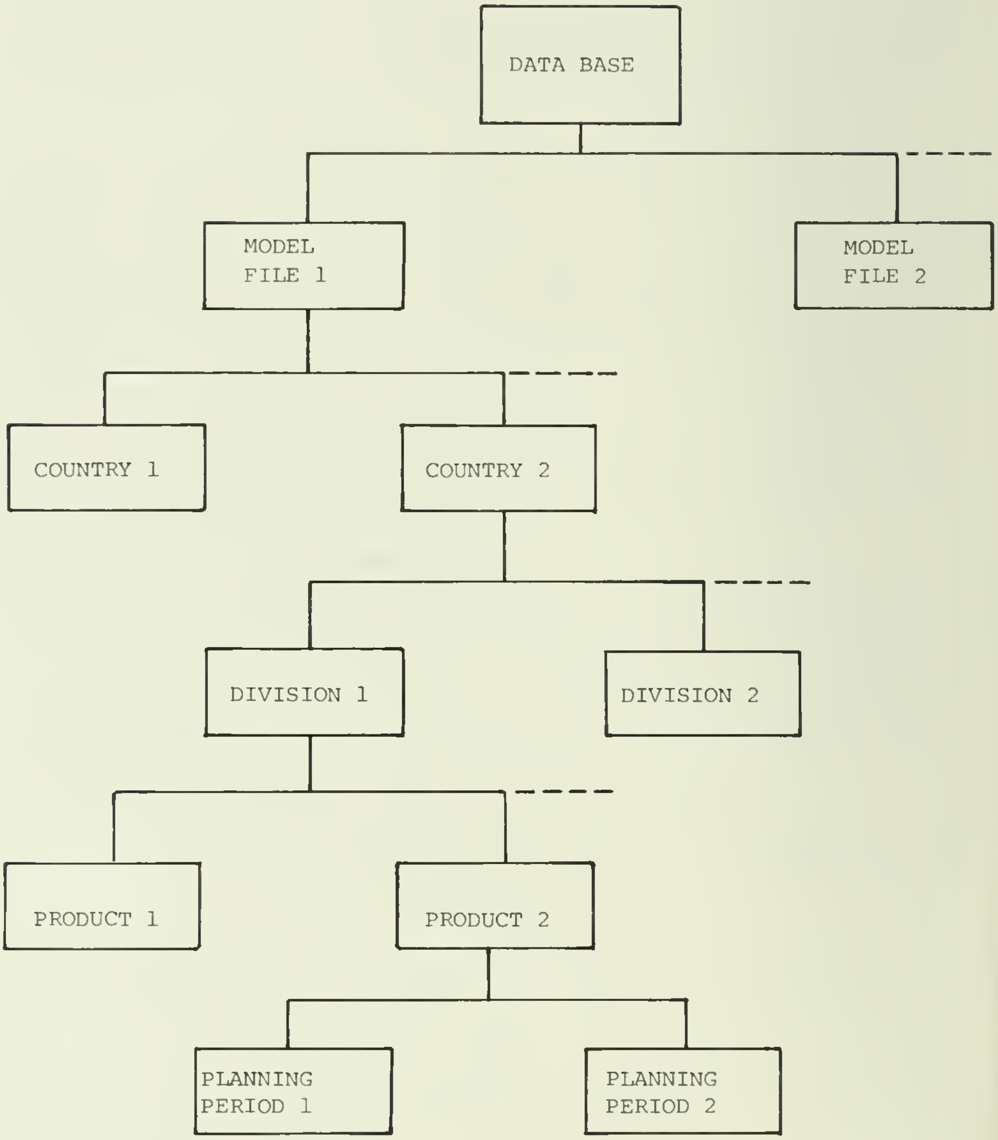
A user may employ several modeling files in the indexed sequential database. Each file has a symbolic name and a password which the user may choose for privacy reasons. Up to four specifications allow access to a specific data item for a given country, division, product and planning period. In addition, the system offers commands and statements which enable the user to work on an aggregated level, such as the divisional or country level, if desired. This is a considerable advantage compared to the primarily line oriented systems previously described.

An in-core calculation matrix is used to perform PLANCODE calculations. Data transfer statements have to be used to read model data from the database into core or to write modeling results back into the database. Statements of the CSPL basically specify operations on rows and columns of the calculation matrix. They are more versatile than with all the languages described so far. PLANCODE allows for indexed variables and as a consequence, one may specify operations involving individual elements, rows, columns or submatrices of the calculation matrix. However, since line operations are most frequently encountered, they are the easiest to specify. Matrices or submatrices of the calculation matrix are defined in so called submatrix definition statements. This may be seen from the following example

```
SMD / COSTS / 50
SMD / $MARG_INC / 50 , COSTS.
```

The first definition statements defines a matrix called COSTS which incorporates fifty lines. The second statement defines matrix $MARG_INC which consists of in total a hundred lines containing the previously defined ma-

Figure 8.7. Structure of PLANCODE/S DATABASE



trix COSTS as a submatrix. The possibility to include submatrices in matrix definition statements allows the coding of tree structures of matrices. This facilitates e.g. all aggregations and disaggregations. However, in contrast to some of the systems described below PLANCODE does not allow for character data and set operations may not be formulated.

PLANCODE matrix statements may not only involve matrices, but also vectors and matrix elements. Multiple assignments, e.g.

COSTS = 0

or totalizations are carried out in these cases as may be seen from the example shown below:

TOTAL_INC = TOTAL_INC + $MARG_INC.

Line variable TOTAL_INC would contain the total of all lines in $MARG_INC.

PLANCODE IF and GOTO statements together with statement labels allow for logical branching in a PLANCODE program. The repetitive evaluation of sequences of statements may be specified by BEGLOOP and ENDLOOP statements in analogy to CALL/AS. Blocks of PLANCODE statements may be organized in subroutines. These may be tested independently and stored in a source file. They may be called from a model during its execution or solution. A PLANCODE INCLUDE statement may be used to incorporate blocks of untranslated statements in a program from the source file.

PLANCODE CALL statements may be employed to directly call on programs which are written in other languages, such as PL/I, COBOL, FORTRAN (only PLANCODE/S), and ASSEMBLER. A user may thus attach software already available in another language to the system or use another programming language for specific modeling tasks.

The modeling software includes a number of built-in procedures for datahandling, rule of thumb extrapolation and interpolation of data series, financial calculations and random number generation to be used with risk analysis models. Software for time series analysis is available as well, but may not directly be called from a PLANCODE program. Separate commands which are not part of the modeling language have to be specified. However, the software has access to lines of the PLANCODE calculation matrix. Polynomial and multiple regression models may be specified and estimated. In addition, software to calculate moving average and exponential smoothing forecasts as well as seasonal adjustments is available.

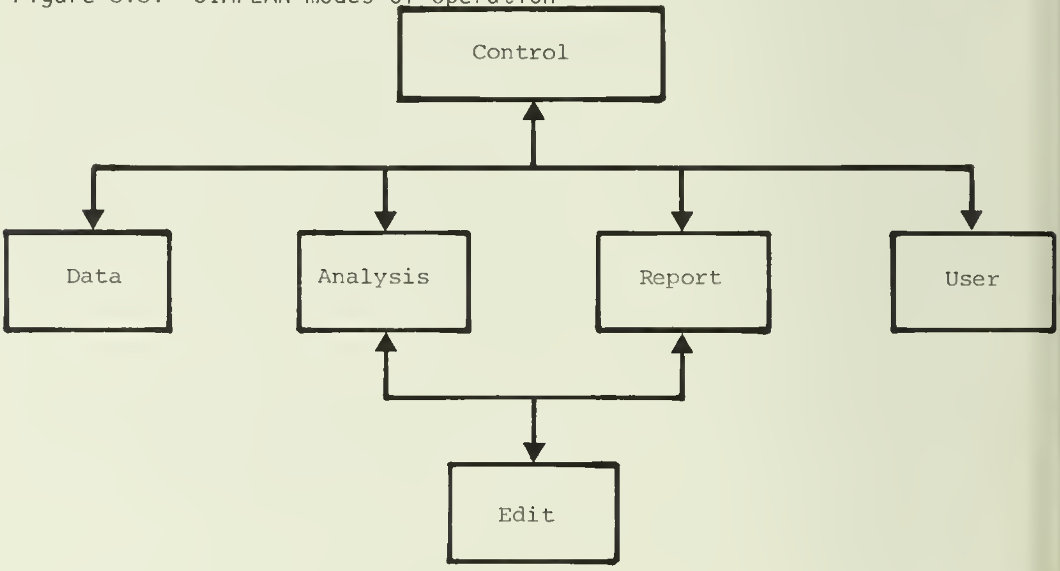
The systems offer an additional language for the specification of standard and non-standard reports and graphical representations. "What if?" experiments may be specified and run quite similar as with the systems pre-

viously described.

SIMPLAN

SIMPLAN is a CSPS developed and offered by the SIMPLAN Group of SSI [59, 50]. SIMPLAN models may either be run in interactive or batch mode. Its application is not restricted to small "ad hoc" models only. Its database structure and management system, modeling language and software allow the construction of all the four, financial, marketing, production, and integrated corporate models. The system operates in several modes as is shown in Figure 8.8.

Figure 8.8. SIMPLAN modes of Operation



The SIMPLAN control mode is employed to enter the other modes of operation. The data mode supports the creation and maintenance of the SIMPLAN database. In addition, it incorporates powerful commands which support data aggregations and consolidations as well as the selection of groups of data series in the database.

The edit mode is entered if a user either wants to specify or modify a SIMPLAN model or report. The SIMPLAN simulation language and modeling commands are used for the first purpose, whereas report commands are used for the specification of customized reports. Both models and reports may be stored in a SIMPLAN text library.

The report mode is entered for the actual generation, but also additional definitions and modifications of reports defined in the edit mode. Models which have been defined in the edit mode are evaluated in the analysis mode. It supports the modeling steps of model estimation, solution, and validation.

Especially far developed with SIMPLAN is an internal security system. In the user mode, one may define and store security levels for data, models, functions and reports together with the levels a certain user may access. This helps preventing an unauthorized use of the system. A company may thus construct an integrated model, e.g. consisting of several divisional models, where central management may experiment with the total model and system, whereas users in the divisions may only control and experiment with their appropriate submodels.

The SIMPLAN database consists of data records which are organized in two dimensions as is shown in Figure 8.9. Its "head" contains numeric and nonnumeric information to characterize the name, type and security level of the data. For a given time period, one may store different versions of numeric data in files of the record. In Figure 8.9, the files of the record could contain profits for different divisions or results obtained from different model runs.

The SIMPLAN data mode incorporates commands which allow the processing of larger quantities and tree structures of data. They may operate on several databases, records or files. The command

```
ADD FILES 1 - 3, 5 - 7 INTO 4, 8 BY 3
```

specifies a multiple file consolidation. For a given record or variable the data contained in files 1, 2, 3 are consolidated and stored in file 4, the data contained in files 5, 6, 7 are added up and stored in file 8. A user may specify in the data report and analysis mode that a command applies to several records. For example, the two commands

```
MASK '***A'
CON INTO TOTASSETS USING 0
```

would specify in the data mode that all records of a database having the character A in the fourth position of their name are consolidated into a record called TOTASSETS, where no use of data previously contained in TOTASSETS is made. A consolidation of files across several records may be called for by a command

```
LET (1) = (2) + (3) FOR C-F.
```

Figure 8.9. SIMPLAN Record

Abbreviation Pro	Record Name PROFITS-Divisions	Units $	Security Level 3

FILE 1					
FILE 2					
FILE 3					
FILE 4					
	1966	1967	1968		1982

For all records whose abbreviation (viz. Figure 8.9) starts with characters between and including C and F files two and three are consolidated into file one.

The SIMPLAN simulation language is mainly line and record oriented. Statements like

INV = INV(-1) + ORD - SALES

usually apply to several columns or time periods. Lags and leads may directly be specified. Individual elements may be addressed by additional specifications. For example, the identifier

PROFITS (3, -1) (1970 - 1973)

would denote four yearly profit values contained in file three of record PROFITS. In a SIMPLAN statement applying to several periods, the 1970 profit value would be used for 1971.

The language allows for logical branching and the repetitive evaluation of groups of SIMPLAN statements. SIMPLAN routines may call on user written PL/I or FORTRAN programs.

The system offers a large amount of software to support the model building process. Practitioner methods are available to extrapolate data series and to perform frequently encountered financial calculations. Descriptive forecasts may be calculated by smoothing methods or trend calculations. The single stage and two stage least squares methods are available for the estimation of econometric models. Risk analysis models may be constructed using random numer generators and both recursive and simultaneous linear and nonlinear models may be solved. Measures of goodness of fit and

predictive accuracy may be calculated in order to discriminate between alternative models.

XSIM

XSIM is an on-line CSPS developed by Dynamics Associates [16]. It is among the furthest developed systems available today and may, like PLAN-CODE and SIMPLAN, be characterized as planning information system with analytical capabilities. With the exception of optimization methods and experimental design techniques it offers practically all the corporate modeling techniques and methods which have been described in previous chapters (viz. e.g. [48, pp. 401-408]). It does not possess automatic language intercommunication facilities which is only a disadvantage if one wants to call e.g. PL/I or FORTRAN programs from a XSIM program. The simulation and modeling languages incorporated by the system are rich in structure and syntax. They should require the use of higher level problem oriented languages only for very specific applications.

XSIM is offered through one of the commercial timesharing networks and incorporates fully integrated commands by which a user may directly access several macroeconomic databases and models. They may in an integrated fashion directly be used together with XSIM corporate models.

Except for the macroeconomic databases, XSIM has access to two other types of files: a random access XSIM database which is used to store data mainly in the form of series or records for on-line modeling purposes, and an indexed sequential XSAM database which may be employed to store large sequences of series as contained in data matrices. The latter may incorporate hierarchical or tree structures as described in chapter 3.

XSIM distinguishes different types of data which may even be mixed in one series or recrod. Normal and high precision numeric data and character data may be employed. An artifical "NA" datatype has been introduced to characterize fields or elements in a series for which data ar not available.

Data entry to XSIM is in free format mainly using terminals. However, especially XSAM files may independently be created, e.g. using special bridge programs and batch mode. Data series and parameters are distinguished. These two separate categories conceptually facilitate the experimentation with alternative parameters of a model. Especially for time series additional attributes allow the identification of their starting and termination date together with their periodicity. Conversion commands allow

transformations between different periodicities (e.g. months, quarters, years).

Data series may be arranged in groups or matrices. Since XSIM incorporates character evaluation commands like character concatenations and substring formation, all the set operations on model variables discussed in chapter 3 may be carried out. Special sorting and screening macros together with statements controlling a repetitive evaluation of statements allow an effective coding of large and possibly hierarchically structured models. For example a search key /ABC/ allows the screening of all model variables contained in the database and incorporating the characters ABC. XSIM databases contain security facilities which protect it from certain types of physical destruction and unauthorized use.

The system in principle incorporates two simulation languages (viz. Figure 8.10): the XSIM language for interactive use is processed command after command in a sequential fashion. The FORTRAN like general programming language XTASK allows the construction of macros and programs consisting of blocks of statements. These may be stored. The XTASK processor either compiles or interprets XTASK statements and produces XSIM commands which may be executed as a block. Special XTASK commands permit the construction of customized interactive XTASK programs which obtain additional terminal input at processing time. However, XTASK programs may also be executed in batch mode. The XTASK language is mainly used for larger models incorporating logical branching (e.g. IF, GOTO statements) and statement repetitions controlled by loop indices and using indexed variables (e.g. LOOP, LOOPEND statements).

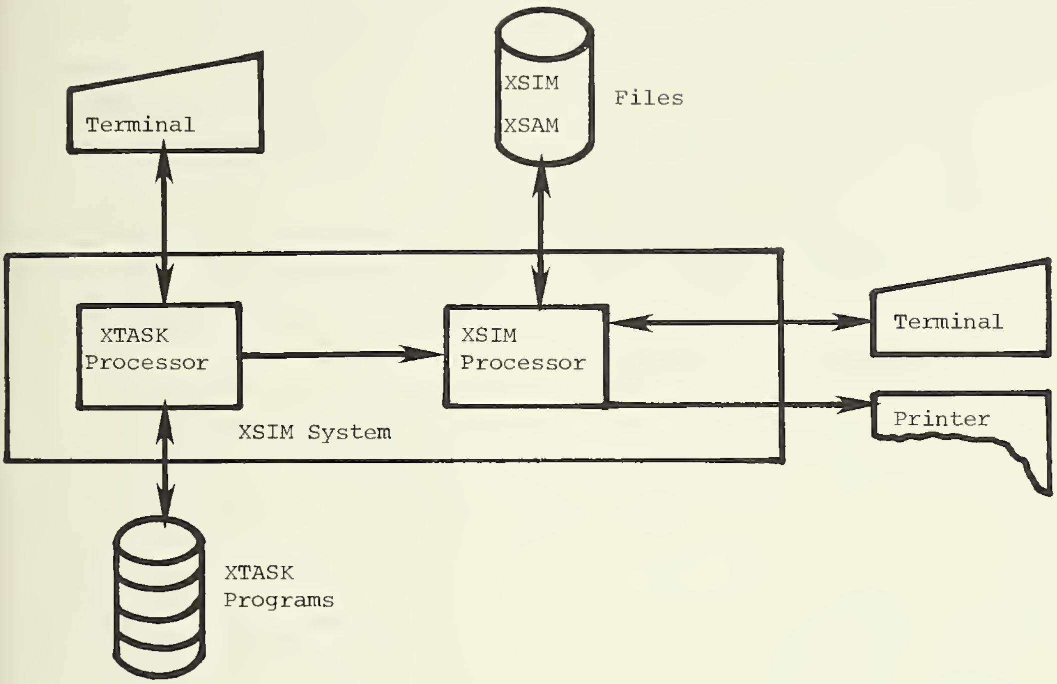
The XSIM language is primarily series oriented like the languages described before. Problems such as dimensions of series and looping within a series which would complicate the coding using a higher level problem oriented language are handled automatically. Statements of the language incorporate the basic arithmetic operations. Variable subscripts to e.g. denote leads and lags are allowed, operators for differencing and percentage changes are available and a variety of builtin functions may be employed. The statement

```
DO     Y = SUM (I = 0 TO -3 : X(I)/4);
```

represents the expression

$$Y = \sum_{i=o}^{n} a_i x_{t-i}, \text{ for } n = 3, \quad a_i = 0.25,$$

Figure 8.10. XSIM System



and gives an impression of the compactness of the XSIM code. Such statements may involve data which are either kept in-core or on the database. Reading and writing operations from and to the database are automized.

The modeling software available in XSIM may be used to construct integrated corporate models with marketing, finance and production submodels. A great number of statistical procedures for a rough data analysis and the specification, estimation, verification and solution of especially econometric models is available. Data needed e.g. in a regression may be specified in a very compact form. The command

REGRESS y , . 'XAMPLE ;

for example specifies that the y series is the dependent variables in a model, where all the variables contained in the group XAMPLE are the independent ones. Model equations for a regression model may be formulated in free-format and may involve data transformations of variables. Estimation methods include multiple linear regression, stepwise regression and

nonlinear regression which may be used with Box-Jenkins and a combination of traditional econometric and Box-Jenkins models. Random number generatore are available for the construction of risk analysis models, special financial functions may be employed for financial submodels. The solution methods allow the solution of single equations and also large systems of nonlinear simultaneous systems of equations. Methods as described in chapter 5 are available to sequence, check and form subgroups of model equations for an effective solution.

Special software allows the continuous and discrete graphical representation of data and modeling results. Report generator commands permit the formulation of output reports which are tailored to the needs of the user.

COMOS CONCEPTS AND SYSTEM

The corporate modeling work carries out at CIBA-GEIGY has been supported by a CSPS called COMOS (Corporate Modeling System). It may be called a planning information system with analytical capabilities. Its main difference to the systems described above is its matrix and table orientation. With this concept it mainly supports larger models with a possibly deeply structured database. COMOS models are mainly operated in batch mode, although especially modifications of the databases and econometric modeling may be carried out in interactive mode using predesigned dialogues. In addition the total system can be run interactively under the IBM Time Sharing Option (TSO).

COMOS CONCEPTS

Corporate Modeling work within CIBA-GEIGY has been going on since 1970. To support the first mainly marketing oriented corporate modeling efforts, an econometric modeling system was initially constructed which was subsequently extended by software and utilities to read, write, and prepare tabular data on external files. In 1973 these developments resulted in a first CSPS called COMOS I (Corporate Modeling System). The system comprised an interpreter which allowed the evaluation of statemnts and macros that were written in a fixed format linear sequential fashion [52].

The statements controlled automatic access to external storage devices and software (econometric routines, linear programming, random numbers, practitioner planning methods). In addition the system was supported by data base utilities and a report generator. In a number of instances it was within hours possible to instruct users not having a backgroundin data processing and quantitative methods how to code simple COMOS I models.

The strictly sequential evaluation of COMOS I commands neither allowed for repetitive evaluation of groups of statements, nor for branching or logical tests: if necessary such tasks had to be accomplished by specially written PL/I-macros. It was also found that the fixed format code was too rigid and the integration of additional software (e.g. experimental designs) not easy to realize. Also extended facilities for model-debugging and error checking were found necessary. Mainly these technical reasons led to the development of COMOS II.

The system as it is presently implemented is intended to support certain types of projects and users:

Type of Models and Projects

Although COMOS II supports the construction of simple models, notably in the financial area, it was more designed to flexibly support the modeling types initially mentioned for models having a bigger data base and a greater number of structural equations. Typically with this type of model the specification of hypotheses and model runs is more likely to be a time-bottleneck than turn-around times between model runs. In a number of more recent applications model parameters and changes to the data base were specified in interactive mode using a screen-terminal. Also certain modeling results may thus be displayed.

However, the steps of the model design procedure are normally carried out in batch-mode. Two points were especially emphasized during the development of the system: first, the COMOS II language should possess a number of heavily aggregated macros and statements which at the same time reduce the number of statements to be written compared to a general purpose language and make the code more transparent and easy to comprehend. Because of these properties models become often more flexible and easier to change than models coded in a general purpose language. Second, using a CALL statement a user should be able to either link fixed blocks of systems software of different degrees of sophistication or routines which

he has prepared himself in COMOS II or PL/I directly to his COMOS model. As such the system should support the construction of management science models "in a favorable software environment".

Type of Users

The systems was designed in such a way that users not having a background in data processing or quantitative methods may themselves specify, run, and test certain models. However, the user's background mainly determines the extent to which he is able code a certain model and to make use of the available software. The present system is not an educational tool in the sense that it teaches a user how to use econometric analysis, experimental designs or mathematical programming [39]. However, the system by its flexibility may support the instruction of users in these methods.

More technically oriented users also profit from the available software. Since the system directly allows for PL/I subroutines, such users may in some instances sacrifice the transparency, flexibility and compactness of a COMOS II calling program for a PL/I program which allows a faster execution. Similarly as with models and methods it largely depends on the user and problem where the exact boundary between COMOS II and PL/I modules is drawn.

Hardware and Software Requirements

A medium to large size IBM Systems/370 configuration is required to install and execute COMOS II. At least one direct access storage drive, one tape drive (for installation purposes only) and one card reader as well as one printer are required.

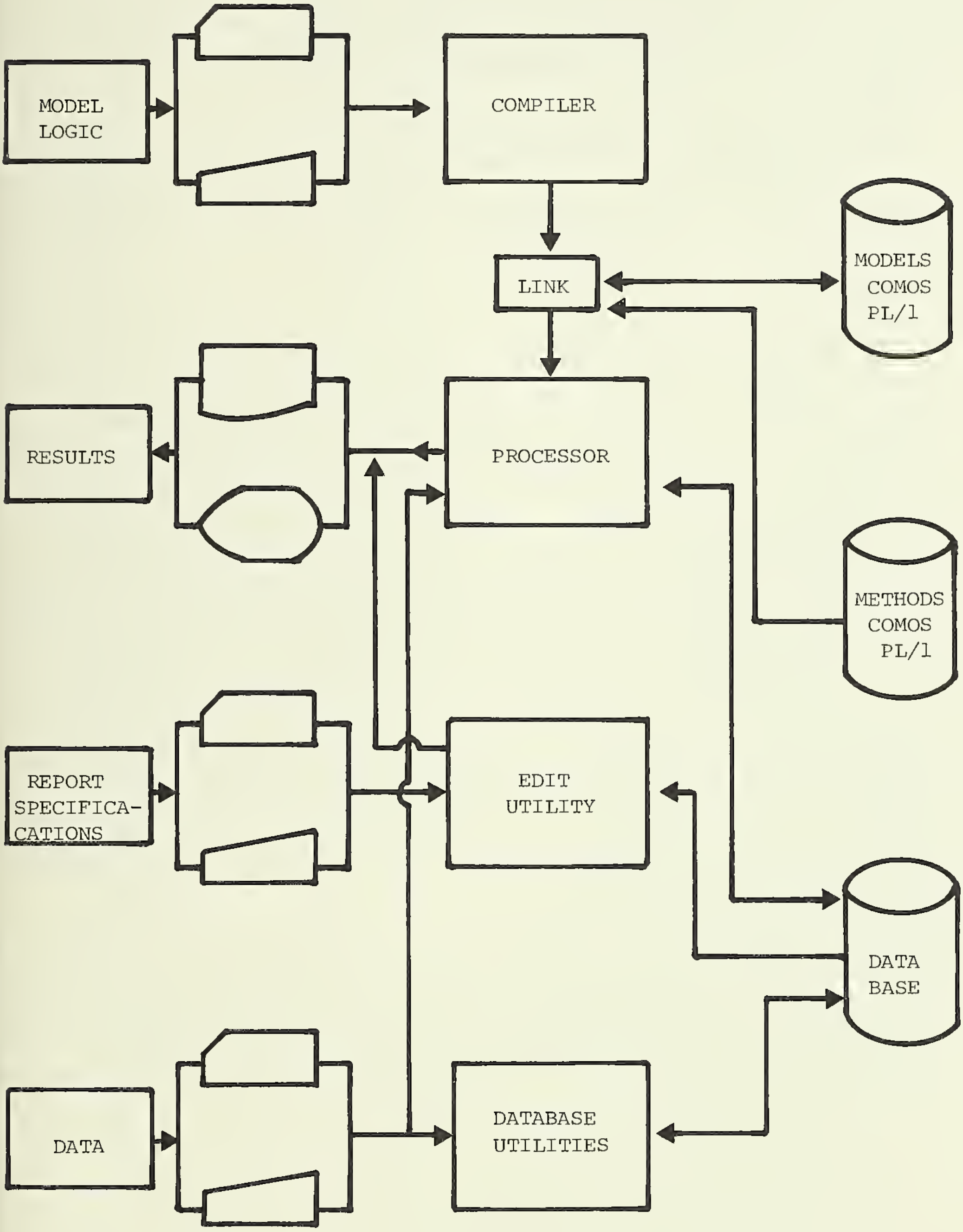
The system is designed to operate as a single task within a partition or region under the control of the IBM System/370 Operation System. A PL/I-Optimizer environment has to be available.

As with COMOS I one may distinuish several COMOS II components (viz. Figure 8.11), notably the

- COMOS II language with tis compiler, linkage editor and processor,
- COMOS II data base, data base utilities and report generator,
- COMOS II software support.

These components are described in the following section.

Figure 8.11. COMOS II components and flow of information



THE COMOS LANGUAGE

One may distinguish the language with its symbols and syntax which defines how COMOS II code has to be written from its realization for a computer with compiler, linkage editor and processor.

The Language

Although similar to PL/I in many aspects, the language possesses a number of special purpose variables and statements which are peculiar to it. An example is shown in Figure 8.12.

Variables

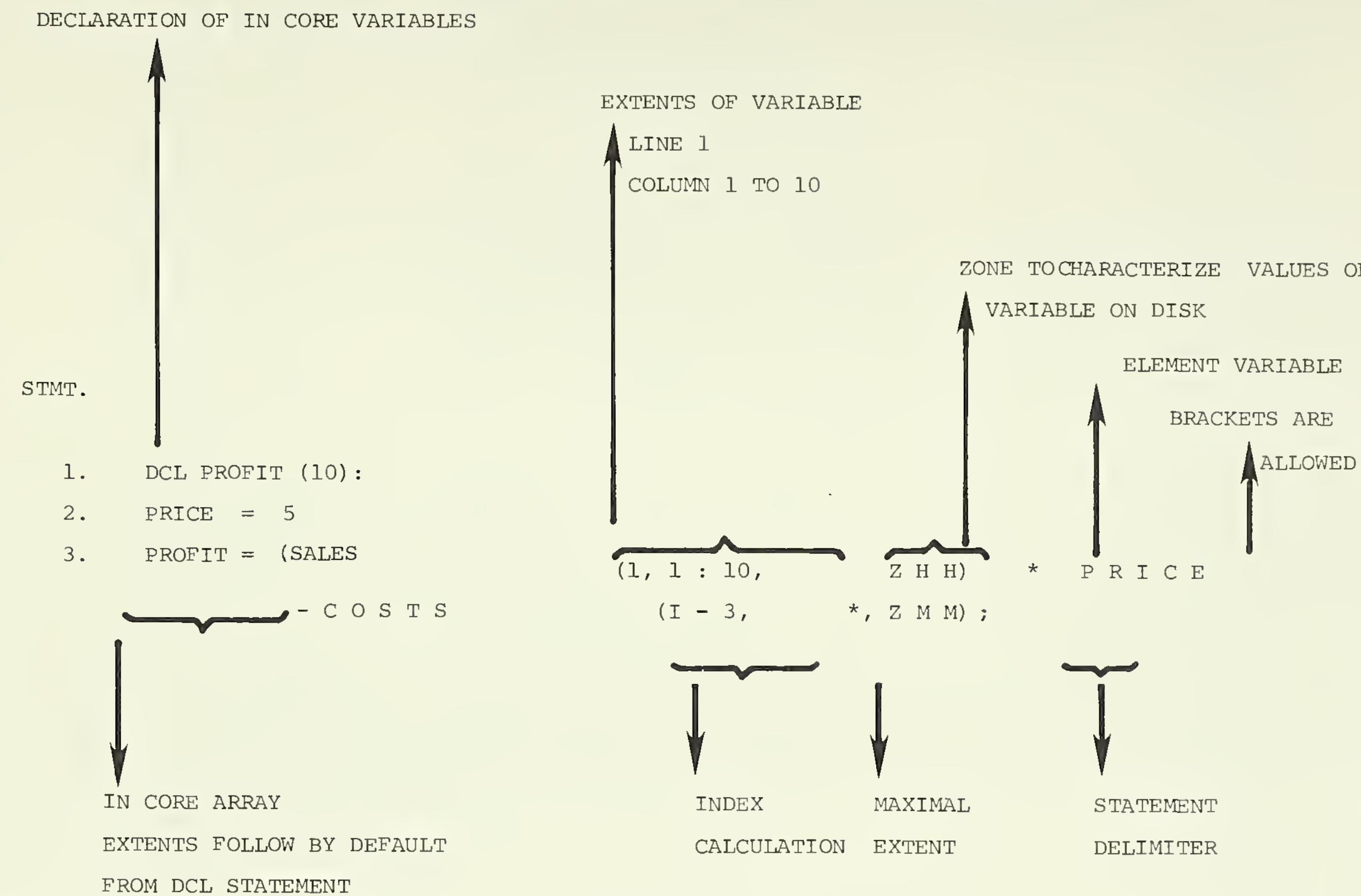
All variables in the example are numeric binary float. The example contains in core elements (PRICE) and arrays (PROFIT (10)) as well as variables whose values are stored on an external disk file (SALES (1,1:10, ZHH), COSTS (I-3,*,ZMM). Apart from binary float variables the system allows for character variables (elements, arrays) of varying length. As with numeric variables one may distinguish between in core character variables and disk character variables. Character variables are of great importance, since they allow the coding of nonnumeric information as may e.g. be contained in variable names (level of aggregation, market segments). The repetitive evaluation of such nonnumeric information may then control numeric evaluations (e.g. tree calculations, set operations). COMOS II disk variables have an eight character identification, identifiers of in core variables may have between one and thirty-one characters. This together with the syntax allows the formulation of natural language like statements.

COMOS II Statements

They allow the specification of a model. Mainly six groups of statements may be distinguished.

- Descriptive Statements, e.g. the DECLARE (DCL) statement describes the attributes of variable, the
  EQUIVALENCE (EQUI) statement allows one to refer with several names to the same variable (viz. Figure 8.13). This capability is of great interest whenever one wants to use a name to describe a certain part of a table or matrix or if one wants to use natural language names to denote a variable.

Figure 8.12. Examples for COMOS II numeric variables, variable declaration and assignment statements



- Computational Statements. The ASSIGNMENT statement controls the evaluation of expressions and assigns their values to certain variables. There is no hierarchy among COMOS II operators, but a sequence of operations may be specified using parantheses. Expressions that do not contain brackets are evaluated left to right. COMOS variables appearing in an assignment statement do not need to possess the same number of subscripts or dimensions. Either an automatic cumulation or a multiple assignement is carried out whenever the dimensions of variables appearing in an assignment statemend do not correspond.
- Data Movement Statements. These control input-output operations from or to terminals, card readers, printers or external files. The PRINT statement in Figure 8.13 controls output to a printer.
- Statements for Sequence Control. The GOTO-statement, a simple arithmetic IF THEN/ELSE-statement , DO-END groups, CALL and RETURN statements are availalbe. Statement lables may be used.
- Storage Control Statements. ALLOCATE/FREE statements allow one to explicitely reserve or free in-core space for variables, the DELETE statement liberates space occupied by COMOS procedures.
- Program Organization Statements. They allow a modular construction of COMOS II models and programs. Procedures are delimited by PROCEDURE and STOP statements. Links to other COMOS procedures are effected using the CALL and RETURN statements.

The Compiler

The COMOS II compiler translates free format COMOS II source code into a concise pseudo object code. There are a great number of different compiler options which are either taken by default or have to be specified by the user. These options support the user in testing, validating and debugging his model. Examples for the output obtained from activating such compiler options are:

- lists of the COMOS II source code with statements numbers (viz. Figure 8.13),
- checks of program syntax. Errors and warnings are signaled using extensive and COMOS specific error messages. Certain types of errors are automatically corrected.
- Cross reference lists for all the variables. These lists contain the names of all the variables and indicate their attributes which

Figure 8.13. Example for COMOS program: determination of single inventory control decisions

```
 1    Order: Procedure (Product, First-Year, Last-Year);
 2           DCL Product;
 3           DCL First_Year;
 4           DCL Last_Year;
 5           Equi Opening_Inventory = Prodopen (Product, year, ZHM);
 6           Equi Sales             = Prodsale (Product, year, ZHM);
 7           Equi Orders            = Prodordr (Product, year, ZHM);
 8           Equi Closing_Inventory = Prodclsg (Product, year, ZHM);
 9           Equi Sales_1           = Prodsale (Product, year-1, ZHM);
10           Equi Sales_2           = Prodsale (Product, year-2, ZHM);
11           Equi Closing_Inventory-1 = Prodclsg (Product, year-1, ZHM);
12           Equi All_Orders        = Prodordr (Product,
                                           First_year: Last_year, ZHM);
13           Year = First_year;
14  Label 1: If year > last_year;
15           Then go to label 2;
16           Opening _ Inventory = Closing_Inventory_1;
17           Sales = (0.7 * Sales_1) + (0.25 * Sales_2);
18           Remaining_Stock = Opening_Inventory - Sales;
19           If Remaining_stock >= 100;
20              Then Orders = 0;
21              Else do;
22                 If Remaining_stock < 0;
23                    Then Orders = 2 * Sales;
24                    Else Orders = 0.5 * (Sales + Sales_1);
25                 End;
26           Closing_Inventory = Opening_Inventory - Sales + Orders;
27           Year = Year + 1;
28           Goto Label 1;
29  Label 2: Print Product, All-Orders;
30           Stop;
```

have either been specified by the user or been taken by default.

The Link Step

After the modules of a COMOS program and PL/I routines connected to it have been compiled the programs are linked together in order to obtain an executable load module.

Both COMOS and PL/I procedures are dynamically, COMOS procedures in addition automatically linked. Thus only those routines are connected which are requested from the actually specified user-macros.

The Processor

Its main characteristics are the following

1. It effects a dynamic storage allocation for variables and subroutine. In contrast to other languages and systems, storage is only allocated after the first invocation of a variables or program. FREE or DELETE statements of the language cause the processor to delete variables and programs from central core.
2. The processor controls direct and auto-matic access to the data base. The compiler already recognizes variables contained in the date base of a model from the indication of a record-zone (viz. Figure 8.12 SALES, COSTS). Whenever the processor encounters a variable contained in the data base (e.g. on disk) it, first, automatically allocates space for it in core, second, accesses and transfers its data from the data base into core, third, performs the operations specified, fourth, if required, rewrites results into data base, and , fifth, liberates the core space of the data base variable. Since these five steps are typically carried out if assignment statements are processed, it is easy to imagine the reduction in the number of statements of the source code compared to a program written in a general purpose language.
3. The processor supplies extensive error messages and debugging aids. Some examples are:
   - automatic subscriptrange tests for vectors and matrices,
   - tests to check whether there is enough core avaiable before a variable or program is allocated ,
   - the processor signales diagnostic messages and the statement number where an error condition is encountered. Also an easy-to-read dump, a detailed version of the COMOS II object code

and the data control blocks are printed out if the user has specified an appropriate processor option and an error has been detected.

- A number of built-in procedures enable the user to follow the execution of a COMOS program, examples being
  - messages to indicate the invocation of a program,
  - specification of dump print-output without an interrupt occuring.

It should be mentioned that all COMOS II keywords, messages and headings are presently written in English. Since such text is centralized and stored on external files a user may easily use another language.

4. Built-In Procedures. A great proportion of the PL/I built-in functions have also been implemented in COMOS II. These built-in procedures do not only include the usual arithmetic functions (e.g. SIN, ABS, MAX, MOD) but also functions related to language facilities (e.g. DATE, manipulation of arrays and character variables, SUBSTR).

A first step towards the evaluation of non-numeric information using set and tree operations has been made possible using the built-in procedure MODNAME. It enables the user to change the identification of a variable. For example the statement

```
CALL MODNAME (TABLE, 'BUDDC1ØØ');
```

assigns the identification TABLE to the disk variable 'BUDC1ØØ' ('Budget Daughter Company No. 100') and reference to this variable may be made using TABLE. The identification 'BUDDC1ØØ' may be an element in a character string array. Having defined an appropriate key orgranization of disk variables and using the COMOS II SUBSTR-, MODNAME built-ins and character concatenation within loops it is relatively easy to perform set operations on the variable identifiers. Sets of identifiers may then control arithmetic operations such as aggregations, disaggregations and tree calcuations.

5. Direct Calls to PL/I Programs. Using a CALL-PL/I statement, e.g.

```
CALL PL/I·SUB1 (PARM1, PARM2, ...);
```

a user may directly access user written PL/I routines and software. The parameters in the CALL-PL/I statement are restricted to BINARY FLOAT and CHARACTER like all COMOS variables.

DATA BASE

One of the most important reasons for the development of COMOS has been the fact that corporate models often require large amounts of data for the modeling process which are difficult to handle without a standardized storage structure and organization as well as standardized update, delete and retrieval routines.

Physical Organization

At present COMOS II uses index-sequential data sets, a matrix or table row essentially corresponding to a record. The system has been developed in such a way that all input-output operations using data base files are centralized in a few routines. If another files organization is chosen, e.g. to adapt the system to another data management system, only these routines have to be changed.

Logical Organization

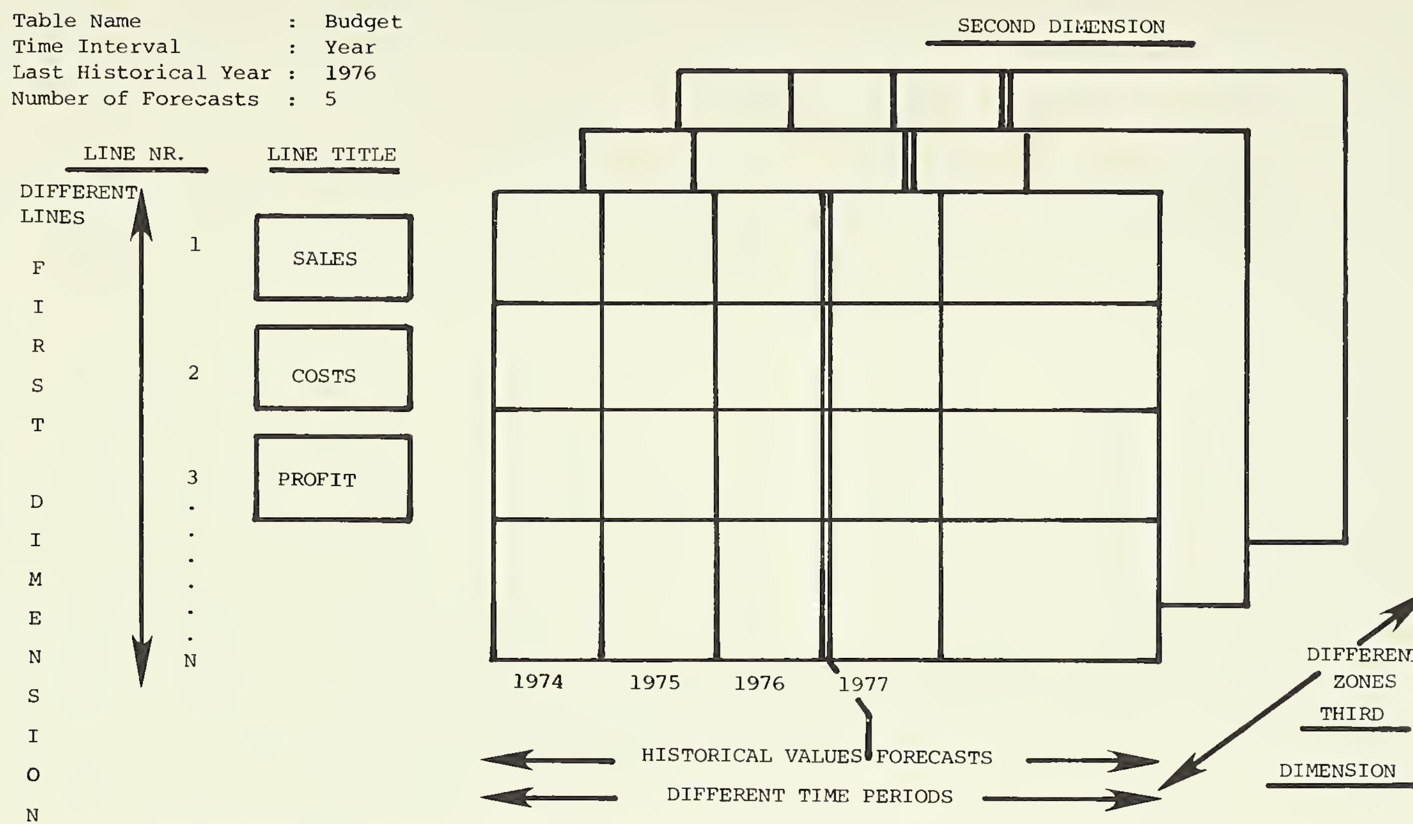
The basic elements are shown in Figure 8.14 which represents the organization of a disk variable with identifier BUDGET.

A COMOS disk variable possesses three dimensions. In most cases a horizontal slice represents a time series which may be referred to by its line number. Lines normally have assigned names to them in order to allow an automatic editing. The time dimension is normally divided into two parts; historical and forecast periods. This concept facilitates the work with time-series-like models. However, it should be noted that the names assigned to columns and lines are arbitrary and under the control of the user. There is no hierarchy of line or column operations.

The third dimension (e.g. zones) may be used for a number of purposes: storage of data base and models zero solution, optimistic, pessimistic and probable solutions, intermediate storage.

The number of columns, lines, and zones may vary from one COMOS variable/table to another. The characteristics of every table (extent, numeric or character, intensive or extensive quantities, number of historic and forecast periods, periodicity) are stored in the first record of every table and may directly be accessed and printed from a COMOS program.

Figure 8.14. Logical organization of COMOS database for numeric data



Report Generation

The system comprises a report generator which allows the editing of data base variables into several standard forms.

Several report generator options permit a specification of

1. the tables to be editied, including
   - parts of tables (lines, columns) and
   - fictitious tables which are combined from several physically existing tables only for output purposes,
   - the zones to be edited,
2. the report organization such as the use of
   - line skipping,
   - insertion of lines,
   - changes to names of lines,
   - percentage and growth rate calculations etc.

A typical report generator output is shown in Figure 8.15.

Data Base Utilities

The software package incorporates several utilities which allow the generation and modifiction of the data base as well as the storage of back up versions.

SOFTWARE SUPPORT OF MODELING STEPS

We have described how the COMOS-compiler supports a model user in the formal and diagnostic checking of the model structure. As such the compiler with the messages and diagnostics it supplies may be considered a validation tool in iteslf. In addition the system at the moment contains approximately 100 software routines which the user may call to support the modeling steps during the COMOS program execution. With respect to programming languages one can distinquish PL/I and COMOS software. Regarding the operations actually carried out, the software comprises something like a method-bank, routines to perform standard-calculations which are more complex than calculations specified by built-in functions of the system, finally a number of routines to specify and call certain standard model structures. The routines and their names are classified and chosen with respect to the steps of the model design procedure. Most of the routines may be used and called on a stand-alone basis from either a COMOS II or another PL/I program. In fact, many of the routines had

Figure 8.15. Typical output for a COMOS sample model

PRODUCT GROUP 5 COUNTRY 9

1973	1974	1975	1976	1977				1978	1979	1980	1981	1982	Mean Growth Rate %
150	160	165	170	175	1	G N P 10**6	$	183	187	192	195	198	2.01
1800	1900	2000	2000	2050	2	Total Market	KG	2122	2151	2173	2190	2204	0.93
190	180	150	280	290	3	Advertising	$	280	280	300	150	150	-18.72
100	100	105	95	90	4	Price	$	95	92	98	102	99	1.85
0.09	0.09	0.08	0.12	0.13	5	Market Share	%	0.11	0.11	0.10	0.09	0.09	-5.53
225	225	225	225	225	6	Capacity	KG	225	225	225	225	225	0.00
0	0	0	0	0	7	Import	KG	3	5	0	0	0	-38.44
10	15	10	0	0	8	Export	KG	0	0	0	15	20	87.03
162	171	160	240	266	9	Demand Country 9	KG	228	249	225	209	202	-4.08
172	186	170	225	225	10	Sales Quantity	KG	225	225	225	225	222	-0.20
17199	18599	17849	21375	20250	11	Sales Value	$	21375	20700	22050	22950	22046	1.65
245	265	242	321	321	12	Quantity Product A	KG	321	321	321	321	318	-0.20
982	1062	971	1285	1285	13	Quantity Product B	KG	1285	1285	1285	1285	1272	-0.20
2702	2922	2670	3534	3534	14	Quantity Product C	KG	3535	3535	3535	3535	3499	-0.20
1204	1302	1249	1496	1417	15	Cost Product A	$	1496	1449	1543	1606	1543	1.65
2064	2232	2142	2565	2430	16	Cost Product B	$	2565	2484	2646	2754	2645	1.65
2322	2511	2409	2885	2733	17	Cost Product C	$	2885	2794	2976	3098	2976	1.65
860	930	892	1068	1012	18	Energy	$	1068	1035	1102	1147	1102	1.65
1720	1860	1785	2137	2025	19	Labor 1	$	2137	2070	2205	2295	2204	1.65
344	372	357	427	405	20	Distribution	$	427	414	441	459	440	1.65
1720	1860	1785	2137	2025	21	Sales Tax	$	2137	2070	2205	2295	2204	1.65
10233	11066	10620	12718	12048	22	Variable Costs	$	12718	12316	13119	13655	13117	1.65
190	180	150	280	290	23	Advertising	$	280	280	300	150	150	-18.72
2120	2300	2550	2800	3000	24	Labor 2	$	3400	3700	4000	4400	4800	8.63
1600	1400	1800	1700	2000	25	Depreciation	$	2000	1600	1200	800	400	-39.11
3000	3000	3000	3000	3000	26	Fixed Tax	$	3000	3000	3000	3000	3000	0.00
6910	6880	7500	7780	8290	27	Period Costs	$	8680	8580	8500	8350	8350	-1.04
56	653	-270	876	-88	28	Marginal Income	$	-23	-196	430	944	578	
0	0	0	0	0	29	Disc. Marg. Income	$	-23	-178	355	645	270	
0	0	0	0	0	30	Present Worth	$	1069	1201	1537	1471	578	

previously been developed for more isolated applications. In the sequel they have been standardized and attached to the system. The system allows for the integration of additional COMOS II and PL/I software. Examples for the types of software presently available or in development are given below:

Data Collection and Preparation

Data Preparation

- Utilities to Create, Delete and Update Data Base
- Plots and Histogramms for data on files and in core
- Cutting, lagging, differencing, deseasonalizing of data series. Generation of trend and dummy series for econometric analysis
- Box-Cox transformation of data series
- Generation of data series for distributed lag estimations (inverted V, Hermite and Lagrange polynomial lag distributions)

Rough Data Analysis

- Calculation of totals, means, standard deviations and maxima as well as minima of data series
- Autocorrelation -, partial autocorrelation - and cross-lag-correlation functions of data series

Estimation, Solution and Simulation

Estimation

- Single stage, two stage and non-linear least squares estimation
- Linear programming estimation
- Forecasting and calculation of confidence intervals

Intuitive Extra/Interpolation

- Linear and exponential extrapolation or interpolation of data series
- Moving averages and exponential smoothing forecasts

Solution

- Matrix Operations
- Gauss-Seidel Method

Optimization

- Revised Simplex and Transportation Method
- Fibonacci-Search
- Hooke-Jeeves Search

Simulation

- Random number generators

Verification, Validation

- Statistical distributions
- Tests of Goodness of Fit
- Variance Analysis
- Tests on autocorrelations, crosscorrelations, and multicollinearity
- Theil's and Wold's coefficients of predictive accuracy

Experimentation [53]

- Local Designs
- Full and Fractional Factorial Designs
- Random Balance Designs
- Rotatable Designs.

The philosophy behind the selection of this software was to give the user a set of robust and frequently encountered macros and at the same time to allow the inclusion of other software tailored more to specific problems. Most of the software was programmed in PL/I because of the higher efficiency of the execution code thus produced; however, a number of solution and optimization methods (e.g. Gauss-Seidel method, Fibonacci-Search) have been programmed in COMOS, because they are of a very simple structure and normally call models which are written in COMOS.

In addition to the software moduls mentioned the system comprises a number of ready-made blocks which consist of groups of such moduls. A user may call these blocks by specifying character codes in a calling COMOS II program. The blocks offer standard solutions to frequently encountered types of modeling steps and models, examples being the data preparation, specification, estimation, solution, and verification of econometric models or the data preparation and solution of linear programming models. Standard models to be used in the first case include a number of intrinsicly linear models (e.g. exponential, double-log, log-reziprocal), but also nonlinear models like generalized logistic or gamma-models for long range trend forecasting [51, 52, 54]. This solution enables users who have little background in data processing to perform some steps of the model design procedure. However, it goes without saying that the concept described only helps in the solution of one type of model-

manager interface problem: more sophisticated methods and models still have to be understood as such and the system does not teach the user how to appropriately use the software available.

CORPORATE MODEL CASE STUDY

An overall impression of the function and application of many COMOS statements may be obtained from the following marketing,production and financial corporate model. It is quite similar to a real world application described in chapter 9.

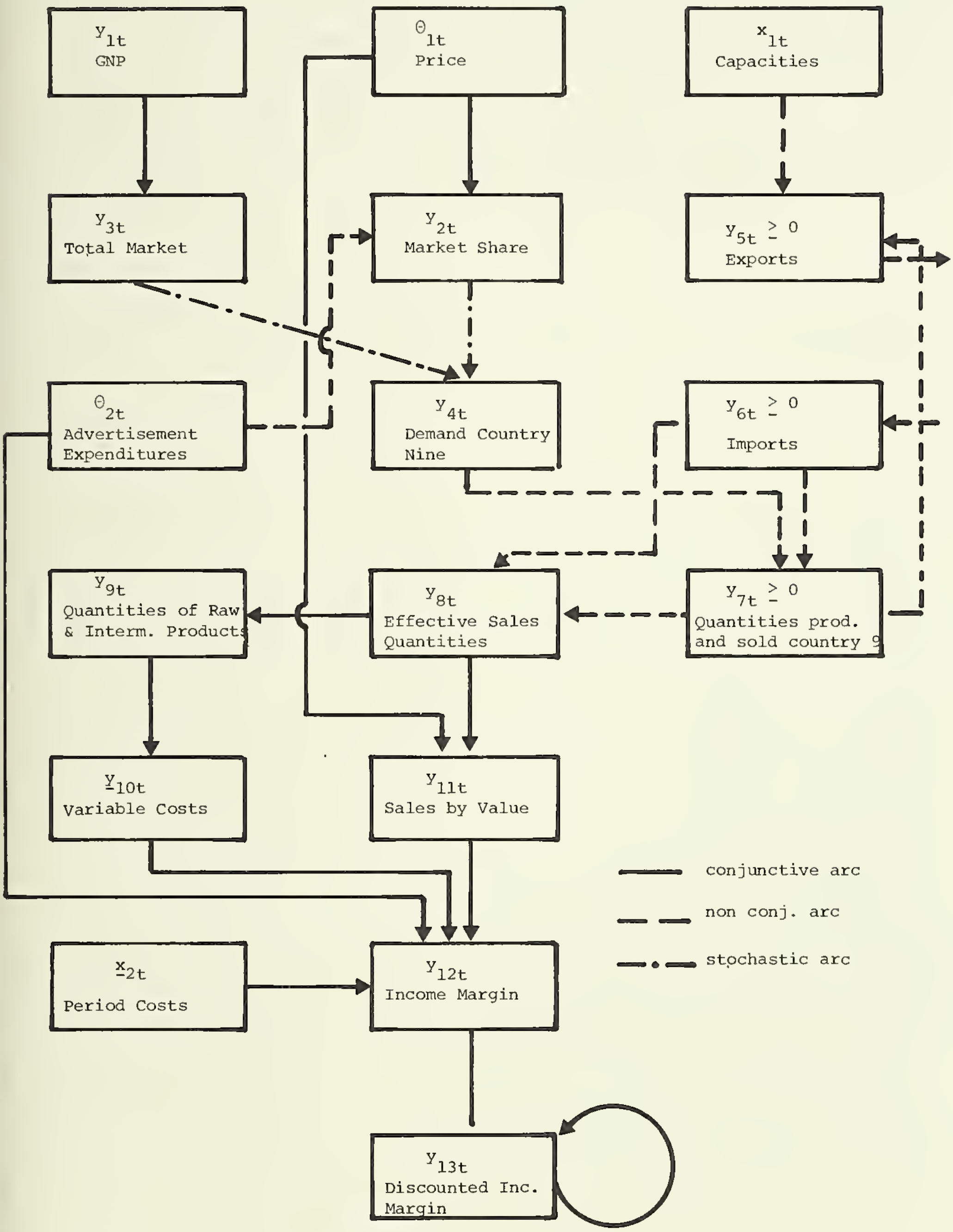
The model deals with two countries (country number nine and country number five) in which a company produces and sells a group of products. Figure 8.16 shows a GESIFLO-graph of the submodel structure for country number nine. The report generator output shown in Figure 8.15 represents an expected model solution. As may be seen from Figure 8.16, the two country models are linked by exports and imports. If the production capacity in one country is not sufficient to fulfill its demand in a given period and the other country at the same time possesses an excess capacity, imports may be used to fill the gap.

The corporate model consists of a marketing submodel in which the demand quantity y_{4t} for a country and product group five is calculated. Econometric models are specified, estimated, simulated, and verified for this purpose. A distribution submodel is used to calculate exports y_{5t}, imports y_{6t} and the effective sales quantities y_{8t} for given transfer prices. A production or activity analysis submodel calculates the quantity of intermediate and raw materials Y_{9t} to produce a known effective sales quantity. Finally, a financial submodel evaluates all the financial figures and consequences related to sales, distribution as well as production and determines discounted income margins and a present worth figure for a five year planning horizon. The submodels are realized by COMOS subroutines which are coordinated by a COMOS control procedure.

Marketing Submodel

Figure 8.17 supplies the historical values for a gross national product variable GNP $\hat{y}_{1t}$, total product market $\hat{y}_{3t}$, market share of product group 5 $\hat{y}_{2t}$, and the two decision variables group-price-index $\hat{\theta}_{1t}$ and advertisement expenditures $\hat{\theta}_{2t}$. Planned values of the decision variables are supplied as well. Econometric single equation models were used

Figure 8.16. GESIFLO-graph of a country submodel.



to estimate forecasts of the GNP, total market, and market share variables. Both expected optimistic and pessimistic forecasts were determined and stored in the COMOS database. The latter were obtained from 90% confidence intervals. Only expected forecasts are shown in Figure 8.17.

Figure 8.17. Historical, Forecast and Plan Values for Marketing Model

1968	100	980	89	200	0.10
1969	105	1010	88	200	0.12
1970	110	1200	90	190	0.10
1971	120	1400	95	150	0.09
1972	140	1700	95	210	0.10
1973	150	1800	100	190	0.09
1974	160	1900	100	180	0.09
1975	165	2000	105	150	0.08
1976	170	2000	95	280	0.12
1977	175	2050	90	290	0.13
1978	183	2122	95	280	0.11
1979	188	2152	92	280	0.11
1980	192	2174	98	300	0.10
1981	196	2191	102	150	0.09
1982	199	2204	99	150	0.09

GNP was estimated and forecasted as a function of time using a nonlinear logictic model. The same type of model was employed to describe the development of the total market; the GNP variable was taken as explanatory variable. Market share was described by a linear model as a function of the price and advertising variables. The latter variable was used with a lag of one year. Figure 8.18 supplies parameter estimates and values of the t-distribution and F-distribution for the three models. Note that the first two models have been estimated by nonlinear regression. A linear regression approximation was used to determine initial parameter estimates. Eight iterations of the Marquardt-Levenberg algorithm were then needed in both cases to attain a convergence limit of $\varepsilon = 0.01$ defined as a mixture of relative and absolute parameter changes.

COMOS econometric models may both be specified and run in batch or interactive mode. Figure 8.19 and 8.20 supply an example for an interactive model and data specification. The dialogue is largely self-explanatory and a 'HELP $\hat{=}$?' symbol is available to print out explanation of the codes used. The program produces the input to a COMOS econometric subpackage which comprises most of the COMOS econometric software procedures. However, they may also be used on a standalone basis and be invoked from any COMOS procedure.

Stochastic Simulation

It should be noted that the COMOS marketing submodel also performs a stochastic simulation. The demand of country 9 (viz. line 9 of Figure 8.15) is defined as the product of the volume of the total market (line 2) and the market share of product group 9 (line 5) or

(8.1) $$y_{4t} = y_{3t} \cdot y_{2t} \text{ .}$$

Expected values and variances of y_{4t} were determined empirically by forming the product described by eq. (8.1). The former was forecasted by the logictic model, the forecasts for the latter were generated by the linear econometric model as a function of the price index (line 4) and advertisement expenditures (line 3) lagged one year. The mean and variance of the distribution function of the demand was determined empirically by multiplying random numbers that described the total market and the market share. Normal random numbers were used as an approximation. Their mean and variance were roughly determined from the interval forecasts for market share and the volume of the total market. The product distribution was again approximately normal and allowed the determination of a 90% confidence interval for the demand. Since COMOS allows the simultaneous calculation and storage of expected optimistic and pessimistic model solutions, only an editing parameter had to be respecified to obtain the optimistic model solution of Figure 8.21. Although the financial results of the expected Figure 8.15 and optimistic solution Figure 8.21 do not deviate appreciably, it is interesting to compare the demand and exports as well as imports in the solutions. Since the demand is in tendency higher than the available production capacities, the financial results are not much affected by changes in the demand.

Figure 8.18: Some statistics to COMOS sample problem

Logistic GNP Model (8 Iterations, $\varepsilon = 0.01$)

	CONSTANT	SATURATION LEVEL	TIME
	0.429	212.6	-0.205
t	(3.16)	(8.74)	(-4.16)

F = 155.5

Logistic Total Market Model (8 Iterations, $\varepsilon = 0.01$)

CONSTANT	SATURATION LEVEL	GNP
3.42	2353.4	-0.031
(6.84)	(13.0)	(-5.45)

F = 169.3

Linear Market Share Model

	CONSTANT	PRICE (0)	ADVERTISING (-1)
	0.307	$-2.27.10^{-3}$	6.10^{-5}
t	(3.46)	(-2.76)	C0.49)

F = 4.98

Distribution Submodel

For the sake of simplicity it is assumed that the long range production capacity in both countries remains constant over a five year planning horizon. It is equal to x_{1t} = 225 (weight units/year) in country number nine. The capacity for product group number five in country five is assumed to be 180 (weight units/year). The forecasted demand for country five is 100, 175, 300, 200 and 200 (units/year), respectively. The two countries may import and export products. The distribution is effected in such a way that the sum of transfer profits in the two countries are maximized. Transfer profits per unit of product group are supposed to be constant over the planning horizon. Figure 8.22 supplies the values that were used for these calculations. The element 10 indicates for example that the firm makes a profit of 10 (monetary units) if a unit of the product group is produced and sold in country 9, the profit is 7 (monetary units) if the

Figure 8.19. Interactive specification of COMOS econometric model

```
ECONOMETRIC ANALYSIS INPUT PROGRAM
ENGLISH - ENTER 1
DEUTSCH - 2 EINTIPPEN
FRANCAIS - ECRIRE 3
? 1
NAME OF MODEL (<= 8 CHARS) ma. share
IS IT NEW (Y/N) y
10 TYPE OF DATA ANALYSIS REQUIRED (0/1/2/3/4/5/6)?
0=NO DATA ANALYSIS            1=TOTALS, MEANS, STDV, MIN, MAX
2=FREQUENCY DISTR, MEANS, ETC   3=CORRELATION MATRIX, T-VALUES
4=AUTO CORRELATION, PARTIAL AUTOCORRELATION, CONFIDENCE LIMITS
5=CROSS-CORRELEATION, CROSS-LAG-CORRELATION AND T-VALUES
6=LIKE 3 WITH FARRAR-GLAUBER TESTS OF MULTICOLLINEARITY
10 TYPE OF DATA ANALYSIS REQUIRED (0/1/2/3/4/5/6) 5
11 NUMBER OF DATA SERIES 3
12 SERIES FOR CONSTANT IN THE ANALYSIS (Y/N) y
13 SERIES FOR POLYNOMIAL TREND (0/1/2/3/4/5/6/7/8/9) ?
0=NO TREND                      1=LINEAR TREND
2-9=DEGREE OF POLYNOMIAL TREND
13 SERIES FOR POLYNOMIAL TREND (0/1/2/3/4/5/6/7/8/9) 0
14 SERIES FOR CYCLES OR DUMMIES (0/1/2/3/4)          0
17 EXPONENTIAL SMOOTHING FOR FIRST SERIES (0/1/2/3) ?
0=NO SMOOTHING                  1=SINGLE EXP. SMOOTHING
2=DOUBLE EXP. SMOOTHING         3=TRIPLE EXP. SMOOTHING
17 EXPONENTIAL SMOOTHING FOR FIRST SERIES (0/1/2/3) 1
19 TYPE OF PARAMETER ESTIMATION WANTED (0/1/2/3) ?
0=NO ESTIMATION                 1=SINGLE STAGE LEAST SQUARES
2=TWO STAGE LEAST SQUARES       3=NONLINEAR LEAST SQUARES
19 TYPE OF PARAMETER ESTIMATION WANTED (0/1/2/3) 1
20 TYPE OF VERIFICATION/VALIDATION WANTED (0/1/2/3) ?
0=NO VERIFICATION               1=DURBIN-WATSON RESIDUAL TEST
2=DURBIN PERIODOGRAM-TEST, COCHRAN-ORCUTT PROCEDURE
3=LIKE 2 WITH WOLD AND THEIL COEFFICIENTS OF PREDICTIVE
ACCURACY USING DATA GIVEN IN 28
20 TYPE OF VERIFICATION/VALIDATION WANTED (0/1/2/3) 2
21 CODE FOR MODEL TO BE ESTIMATED (0-8 ARE STANDARD) ?
0=LINEAR                        1=EXPONENTIAL
2=DOUBLE LOG                    3=LOG-RECIPROCAL
4=EXPONENTIAL SATURATION        5=LOGISTIC
6=BERTHALANFFY                  7=GOMPERTZ
8=GAMMA                         9=BY USER ROUTINE @PLIFUN
21 CODE FOR MODEL TO BE ESTIMATED (0-8 ARE STANDARD) 0
26 PROBABILITY LEVEL FOR FORECASTS (90/95/99) 95
27 STORAGE IN DATA BASE REQUIRED (Y/N) y
28 ZONE TO STORE LOW FORECAST (Z+M/O/P/H/X+M/O/P/H/X) ?
MAY NOT BE THE SAME ZONE AS THE ONE CONTAINING
THE HISTORICAL VALUES OF THE DEPENDANT SERIES
(QUEST 43)

28 ZONE TO STORE LOW FORECAST (Z+M/O/P/H/X+M/O/P/H/X) zpp
29 ZONE TO STORE MODEL VALUES (Z+M/O/P/H/X+M/O/P/H/X) zmm
30 ZONE TO STORE HIGH FORECAST (Z+M/O/P/H/X+M/O/P/H/X) zoo
31 WHAT OUTPUT REQUIRED (0/1/2/3) ?
0=ALL FOR NONLINEAR ESTIMATIONS ONLY FINAL STATISTICS
1=NO PRINTOUT   2=FOR TWO STAGE AND NONLINEAR, ALL STAGE OUTPUT AND
ITERATION  3=ONLY STATISTICS FOR SECOND STAGE OF TWO STAGE
```

Figure 8.20. Interactive specification of model data for COMOS econometric analysis

```
40 NAME OF DATA SERIES (8 CHARS) ma. share
41 DATA FOLLOWS (Y/N)n
43 DATA BASE ZONE (Z+M/O/P/H/X+M/O/P/H/X) zhh
44 DATA BASE LINE 5
45 DATA BASE FIRST COL 1968
46 DATA BASE LAST COL 1977
57 TRANSFORMATION REQUIRED (Y/N) ?
BOX-COX TRANSFORMATION OF SERIES
57 TRANSFORMATION REQUIRED (Y/N) n
59 NUMBER OF DIFFERENCING OR SMOOTHING OPERATIONS (0/1/2/3) ?
THE GIVEN NUMBER OF OPERATIONS IS CARRIED OUT IN THE
ORDER SPECIFIED
59 NUMBER OF DIFFERENCING OR SMOOTHING OPERATIONS (0/1/2/3) 0
66 NUMBER OF FORECASTING PERIODS 5
40 NAME OF DATA SERIES (8 CHARS) price
41 DATA FOLLOWS (Y/N) y
42 NUMBER OF VALUES 15
89 88 90 95 95 100 100 105 95 90 95 92 98 102 99
47 SHIFT OF BASE VALUE OF SERIES 0
49 LAG (<=0) OR LEAD (>0) OF DATA SERIES 0
50 TYPE OF LAG DISTRIBUTION (0/TR/LO/HO)?
0=NONE             TR=TRIANGULAR LAG DISTRIBUTION
LO=LAGRANGE POLYNOMIAL DISTRIBUTION
HO=HERMIT POLYNOMIAL DISTRIBUTION
50 TYPE OF LAGE DISTRIBUTION (0/TR/LO/HO) 0
57 TRANSFORMATION REQUIRED (Y/N) n
59 NUMBER OF DIFFERENCING OR SMOOTHING OPERATIONS (0/1/2/3) 0
40 NAME OF DATA SERIES (8 CHARS) advert
41 DATA FOLLOWS (Y/N) y
42 NUMBER OF VALUES 15
200 200 190 150 210 190 180 150 280 290 280 280 300 150 150
47 SHIFT OF BASE VALUE OF SERIES o
49 LAG (<=0) OR LEAD (>0) OF DATA SERIES 0
50 TYPE OF LAG DISTRIBUTION (0/TR/LO/HO) #49
49 LAG (<=0) OR LEAD (>0) OF DATA SERIES -1
50 TYPE OF LAG DISTRIBUTION (0/TR/LO/HO) 0
57 TRANSFORMATION REQUIRED (Y/N) 0
57 TRANSFORMATION REQUIRED (Y/N) n
59 NUMBER OF DIFFERENCING OR SMOOTHING OPERATIONS (0/1/2/3) 0
MA. SHARE SAVED
```

Figure 8.21. Optimistic solution of corporate model case study

PRODUCT GROUP 5 COUNTRY 9 OPTIMIST

1973	1974	1975	1976	1977				1978	1979	1980	1981	1982	Mean Growth Rate %
150	160	165	170	175	1	G N P 10**6	$	196	203	210	217	222	3.14
1800	1900	2000	2000	2050	2	Total Market	KG	2290	2331	2363	2389	2410	1.27
190	180	150	280	290	3	Advertising	$	280	280	300	150	150	-18.72
100	100	105	95	90	4	Price	$	95	92	98	102	99	1.85
0.09	0.09	0.08	0.12	0.13	5	Market Share	%	0.14	0.15	0.13	0.13	0.12	-4.63
225	225	225	225	225	6	Capacity	KG	225	225	225	225	225	0.00
0	0	0	0	0	7	Import	KG	79	5	0	84	0	-59.27
10	15	10	0	0	8	Export	KG	0	0	0	0	0	0.00
162	171	160	240	266	9	Demand Country 9	KG	304	328	305	309	262	-3.56
172	186	170	225	225	10	Sales Quantity	KG	225	225	225	225	225	0.00
17199	18599	17849	21375	20250	11	Sales Values	$	21375	20700	22050	22950	22275	1.85
245	265	242	321	321	12	Quantity Product A	KG	321	321	321	321	321	0.00
982	1062	971	1285	1285	13	Quantity Product B	KG	1285	1285	1285	1285	1285	0.00
2702	2922	2670	3534	3534	14	Quanityt Product C	KG	3535	3535	3535	3535	3535	0.00
1204	1302	1249	1496	1417	15	Cost Product A	$	1496	1449	1543	1606	1559	1.85
2064	2232	2142	2565	2430	16	Cost Product B	$	2565	2484	2646	2754	2673	1.85
2322	2511	2409	2885	2733	17	Cost Product C	$	2885	2794	2976	3098	3007	1.85
860	930	892	1068	1012	18	Energy	$	1068	1035	1102	1147	1113	1.85
1720	1860	1785	2137	2025	19	Labor 1	$	2137	2070	2205	2295	2227	1.85
344	372	357	427	405	20	Distribution	$	427	414	441	459	445	1.85
1720	1860	1785	2137	2025	21	Sales Tax	$	2137	2070	2205	2295	2227	1.85
10233	11066	10620	12718	12048	22	Variable Costs	$	12718	12316	13119	13655	13253	1.85
190	180	150	280	290	23	Advertising	$	280	280	300	150	150	-18.72
2120	2300	2550	2800	3000	24	Labor 2	$	3400	3700	4000	4400	4800	8.63
1600	1400	1800	1700	2000	25	Depreciation	$	2000	1600	1200	800	400	-39.11
3000	3000	3000	3000	3000	26	Fixed Tax	$	3000	3000	3000	3000	3000	0.00
6910	6880	7500	7780	8290	27	Period Costs	$	8680	8580	8500	8350	8350	-1.04
56	653	-270	876	-88	28	Marginal Income	$	-23	-196	430	944	671	
0	0	0	0	0	29	Disc. Marg. Income	$	-23	-178	355	645	313	
0	0	0	0	0	30	Present Worth	$	1112	1249	1590	1555	671	

unit is produced in country 9 and exported to country 5.

Figure 8.22: Transfer price matrix for COMOS example

		Production	
		country 9	country 5
Sales	country 9	10	5
	country 5	7	20

Inequalities or non-conjunctive relations are used to express the distribution relations. A country may not export and import at the same time. The quantity of product group five produced and sold in country nine is described by

(8.2) $$y_{7t} \leq y_{4t} - y_{6t} \quad ,$$

exports are defined by

(8.3) $$y_{5t} \leq x_{1t} - y_{7t} \quad .$$

Similar relations hold for country five and form the restrictions of a transportation problem. Its objective function has been formulated using the transfer prices given in Figure 8.22. Figure 8.23 shows the COMOS procedure for the distribution submodel. Results are stored and printed from database-tables COUNTRY5 and COUNTRY9 (viz. lines 400-450). The transfer prices are kept in an in-core matrix called PROFITS. Note that the transportation algorithm is called by the CALL statement in lines 350-380.

Production Submodel

The production of a unit of product group five requires a raw material input C and quantities of intermediate products A and B. The production process is assumed to be cyclical, i.e. a proportion of the finished product group 5 is fed back into the lower production stages. Since variable costs are incurred in all stages of the production process, a parts requirement problem has to be solved by matrix inversion in order to be able to calculate the appropriate cost figures. A matrix of explosion factors is

Figure 8.23. COMOS procedure for distribution submodel

```
$$
 DISTRIBU: PROCEDURE (TIME1, TIME2);
0/*      COMOS PROCEDURE TO CALCULATE EXPORT-IMPORTS                  */
 /*      FOR GIVEN CAPACITIES, DEMAND AND TRANSFER PRICES             */
 /*      IN COUNTRIES FIVE AND NINE                                   */
0        DCL TIME1;
         DCL TIME2;
0        DCL TABLE-NAME-AND-ZONE  CHAR (11);   /* NOT USED,           */
                                              */ DATA IS IN CORE      */
         DCL TYPE-OF-PROBLEM    CHAR (3);
         DCL MODE-OF-ACCESS     CHAR (1);
         DCL PROFITS (4, 4);
         DCL RESULTS (3, 3);
         DCL SOLUTIONS-REQUIRED
         DCL OUTPUT-OPTION;
0  *     INITIALIZATION                                               */
0        TYPE_OF_PROBLEM = 'MAX';         /* MAXIMIZATION             */
         MODE_OF_ACCESS = 'C';            /* MATRIX IS IN CORE        */
         SOLUTIONS_REQUIRED = 1;          /* OPTIMAL SOLUTION         */
         OUTPUT_OPTION = 1;           /* OUTPUT TO BE PRINTED         */
0        PROFITS (1, 1) = 10;
         PROFITS (1, 2) =  5;
         PROFITS (2, 1) =  7;
         PROFITS (2, 2) = 20;
1/*      LOOP OVER ALL PERIODS, FROM TIME1 TO TIME2                   */
0        YEAR = TIME1;
0LABEL1: IF YEAR > TIME2;
           THEN GOTO LABEL2;
0/*      FILL IN DEMAND AND CAPACITIES                                */
0        PROFITS (1, 4) = COUNTRY9 (9, YEAR, ZHM);
         PROFITS (2, 4) = COUNTRY5 (9, YEAR, ZHM);
         PROFITS (4, 1) = COUNTRY9 (6, YEAR, ZHM);
         PROFITS (4, 2) = COUNTRY5 (6, YEAR, ZHM);
0/*      CALL TRANSPORTATION ALGORITHM                                */
0        CALL SOTRAN
           (TYPE_OF_PROBLEM, MODE_OF_ACCESS,
            TABLE-NAME-AND-ZONE, PROFITS,
            RESULTS, SOLUTIONS-REQUIRED, OUTPUT-OPTION);
0/*      DISTRIBUTION OF RESULTS TO EXPORTS-IMPORTS-QUANTITY          */
0        COUNTRY9 (10,YEAR,ZHM) = RESULTS (1,1) + RESULTS (2,1) ;
         COUNTRY5 (10,YEAR,ZHM) = RESULTS (2,2) + RESULTS (1,2) ;
         COUNTRY5 ( 8,YEAR,ZHM) = RESULTS (1,2);
         COUNTRY9 ( 8,YEAR,ZHM) = RESULTS (2,1);
         COUNTRY5 ( 7,YEAR,ZHM) = RESULTS (2,1);
         COUNTRY9 ( 7,YEAR,ZHM) = RESULTS (1,2);
0        YEAR = YEAR + 1;
         GOTO LABEL;
0LABEL2: STOP;
```

given in Figure 8.24. The elements of the matrix indicate the quantity requirements of the product indicated in a line to produce one unit of the product indicated in a column. It needs for example 4 units of intermediate product B to produce one unit of product group 5. The matrix inversion is performed by a call to a COMOS software procedure. The requirements for raw and intermediate products have been printed out in lines 12-14 of the report generator outputs Figure 8.15 and 8.21.

Figure 8.24: Explosion factors for material requirement problem

	Group 5 Product	Intermed. Product A	Intermed. Product B	Raw Product C
G5	0	1	0.05	0
A	1	0	0	0
B	4	0	0	0
C	0	3	2	0

Financial Submodel

It is assumed that the unitcosts for the production of a unit of intermediate products A and B is 0.07 and 0.12 (monetary units), respectively. The purchase price of one unit of raw product C is taken as 0.135 (monetary units) over the whole planning horizon.

The variable costs for product group 5 in country 9 are further decomposed into energy, labour and distribution costs and a proportional sales tax. The appropriate unit costs are 0.05, 0.1, 0.02 and 0.10 (i.e. 10%) of the sales values. The output from the econometric models, the transportation and parts requirement problems are fed into a financial model that calculates the income margin for the product group over the five year planning horizon. Figures 8.15 and 8.21 show two model solutions. The income margin is calculated as the difference between sales by value (line 11) and the sum of variable and period costs. The latter are with the exception of advertisement expenditures an exogenous input to the model. The

Figure 8.25. COMOS procedure for financial subtotal

```
$$
 FINANCE: PROCEDURE (TIME1, TIME2);
0/*       COMOS PROCEDURE TO CALCULATE VARIABLE COSTS                  */
 /*       PERIOD COSTS AND MARGINAL INCOME                             */
0         DCL TIME1;
          DCL TIME2;
0         DCL CORE_HELP (TIME2);
          DCL GROWTH_RATE;
          DCL DISCOUNTING_FACTOR;
          DCL RAW_PRICE (3);
0         EQUI ADVERTISING     = COUNTRY9 (3, TIME1:TIME2, ZHM);
          EQUI SALES_VALUE     = COUNTRY9 (11,TIME1:TIME2, ZHM);
          EQUI QUANT_PROD_A    = COUNTRY9 (12,TIME1:TIME2, ZHM);
          EQUI QUANT_PROD_B    = COUNTRY9 (13,TIME1:TIME2, ZHM);
          EQUI QUANT_PROD_C    = COUNTRY9 (14,TIME1:TIME2, ZHM);
          EQUI COST_PROD_A     = COUNTRY9 (15,TIME1:TIME2, ZHM);
          EQUI COST_PROD_B     = COUNTRY9 (16,TIME1:TIME2, ZHM);
          EQUI COST_PROD_C     = COUNTRY9 (17,TIME1:TIME2, ZHM);
          EQUI LABOR_1         = COUNTRY9 (19,TIME1:TIME2, ZHM);
          EQUI DISTRIBUTION    = COUNTRY9 (20,TIME1:TIME2, ZHM);
          EQUI SALES_TAX       = COUNTRY9 (21,TIME1:TIME2, ZHM);
          EQUI VARIABLE_COSTS  = COUNTRY9 (22,TIME1:TIME2, ZHM);
          EQUI ADVERT_COSTS    = COUNTRY9 (23,TIME1:TIME2, ZHM);
          EQUI LABOR_2         = COUNTRY9 (24,TIME1:TIME2, ZHM);
          EQUI DEPRECIATION    = COUNTRY9 (25,TIME1:TIME2, ZHM);
          EQUI FIXED_TAX       = COUNTRY9 (26,TIME1:TIME2, ZHM);
          EQUI PERIOD_COSTS    = COUNTRY9 (27,TIME1:TIME2, ZHM);
          EQUI MARGINAL_INCOME = COUNTRY9 (28,TIME1:TIME2, ZHM);
1/*       CALCULATE PERIOD COSTS                                       */
 /*       ADVERTISING FROM ECONOMETRIC ANALYSIS                        */
0         ADVERTISING_COSTS = ADVERTISING;
0/*       LABOR2 EXTRAPOLATED WITH GROWTH RATE OF                      */
 /*       TWO LAST HISTORICAL PERIODS                                  */
0         CORE-HELP (*) = COUNTRY9 (24, 1:TIME2, ZHM);
          CORE-HELP (1:TIME1-3) = 1
0         CALL SXEXTR
            (CORE-HELP, TIME2, 3);
0         LABOR_2  = CORE-HELP (TIME1:TIME2);
0/*       DEPRECIATION LINEARILY INTERPOLATED TO A VALUE               */
 /*       OF 400 AT THE END OF THE PLANNING PERIOD                     */
0         CORE_HELP (*) = COUNTRY9 (25, 1:TIME2, ZHM);
          CORE_HELP (TIME2) = 400;
0         CALL  SXINTE
            (CORE_HELP, TIME2, 2);
0         DEPRECIATION = CORE_HELP (TIME1:TIME2);
0/*       FIXED TAX STAYS CONSTANT                                     */
0         FIXED_TAX = COUNTRY9 (26, TIME1-1, ZHM);
0/*       CALCULATE TOTAL PERIOD COSTS                                 */
0         PERIOD_COSTS = COUNTRY9 (23:26, TIME1:TIME2, ZHM);
0/*       CALCULATE VARIABLE COSTS                                     */
```

Figure 8.25. Continued

```
 /*      NO CHANGES IN PRICES OF RAW AND INTERMEDIATE PRODUCTS */
0        RAW_PRICE (*) = COUNTRY9 (15:17, TIME1-1, ZHM) /
           COUNTRY9 (12:14, TIME1-1, ZHM);
0        COST_PRODUCT_A = RAW-PRICE (1) * QUANTITY_PRODUCT_A;
         COST_PRODUCT_A = RAW_PRICE (2) * QUANTITY_PRODUCT_B;
         COST_PRODUCT_A = RAW_PRICE (3) * QUANTITY_PRODUCT_C;
1/*      ENERGY COSTS INCREASE BY 5% P.A. OVER LAST VALUE      */
0        YEAR = TIME1;
         GROWTH_RATE = 1;
0LABEL1= IF YEAR > TIME2;
           THEN GOTO LABEL2;
0        GROWTH_RATE = GROWTH_RATE * 1.05;
         COUNTRY9 (18, YEAR, ZHMO = COUNTRY9 (18, YEAR-1, ZHM) *
           GROWTH_RATE;
         YEAR = YEAR + 1;
         GOTO LABEL1;
0/*      LABOR COSTS 8%, DISTRIBUTION COSTS 2% and             */
 /*      SALES TAX 10% OF SALES VALUES                         */
0LABEL2= LABOR_1 = 0.08 * SALES_VALUE;
         DISTRIBUTION = 0.02 * SALES_VALUE;
         SALES_TAX = 0.10 * SALES_VALUE:
0/*      CALCULATE TOTAL VARIABLE COSTS                        */
0        VARIABLE_COSTS = COUNTRY9 (15:21, TIME1:TIME2, ZHM);
0/*      CALCULATE INCOME MARGIN                               */
0        MARGINAL_INCOME = SALES_VALUE - VARIABLE_COSTS -
                                          PERIOD-COSTS;
0/*      DISCOUNT INCOME AT 12% AND CALCULATE PRESENT WORTH    */
0        YEAR = TIME1;
         COUNTRY9 (30, TIME1, ZHM) = 0;
         DISCOUNTING_FACTOR = 1;
0LABEL3: IF YEAR > TIME2;
           THEN GOTO LABEL4;
0        COUNTRY9 (29, YEAR, ZHM) = COUNTRY9 (28, YEAR, ZHM)/
           DISCOUNTING_FACTOR;
         COUNTRY9 (30, TIME1, ZHM) = COUNTRY9 (30, TIME1, ZHM) +
           COUNTRY9 (29, YEAR, ZHM);
         DISCOUNTING_FACTOR = DISCOUNTING_FACTOR * 1.12;
         YEAR = YEAR + 1;
         GOTO LABEL3;
0LABEL4: STOP;
```

figures also show annual values for the discounted income margin. The discount rate used was 0.1 (i.e. 10% p.a.). The present worth of income margin of the product group is 1069.25 (monetary units) for 1978. Figure 8.25 shows a COMOS procedure for the financial submodel. Some figures and hypothesis have been changed compared to the orginal program used to generate Figure 8.15 and 8.21. English language like statements without indices may be used to code most of the identities. The EQUI statements shown may be stored away and a user may work with line variables similar to most of the other CSPSs previously described.

CONCLUSIONS AND FUTURE DEVELOPMENTS

Experience has shown that CSPSs like COMOS II may indeed be used for the construction of corporate models. CSPSs tend to involve the user more directly in the modeling process than would be possible if models were entirely programmed in a general purpose language. The extent to which a user becomes involved in the modeling process largely depends on the nature of the corporate modeling project and the user's background. There is enough evidence available to show that many users, especially with budgeting or financial planning and simulation models, have learned how to employ models as an experimental tool. Such models allow the evaluation of more alternatives and more timely information than was possible with manual methods and traditional financial information systems. Model builders have on one hand learned how to build relevant models and on the other hand how to give answers to certain types of management questions (viz e.g. Naylor [47]). CSPSs often allow a more flexible, more compact and transparent model coding. Comparing compile and run times sometimes also systems stability, with a model employing a general purpose language, one may have to take certain disadvantages of using a CSPS into account. But on the whole using CSPSs should also be more economical from the model builders point of view.

However, there is still room for improving the existing systems. Regarding methodological requirements of corporate modeling, the software described in previous chapters is thought to be sufficient, but its application often requires more knowledge about methods than is actually necessary from the users side. Asking for, checking, and correcting errors

in model and parameter specifications, notably in the area of econometric model building, may be done in interactive mode. 'Menu' programs, prompting and help commands which display part of the model, methods and systems documentations help improving the modeling process and a number of CSPSs incorporate such aids [9, 13, 16, 57, 58, 60]. But it is believed that such means may still be further developed. Further implementation research is necessary to determine what type of users and problems may be supported by which type of customized dialogue. Possibly future CSPSs should incorporate properties of self-teaching packages as well.

It has been argued before that especially for the strategic planning process a user should exploit his a priori knowledge about planning problems which he does not necessarily posses in a quantitative form. Future CSPSs should perhaps give more support to users working informally with hunches and mere guesses in the different modeling steps. New software developments and even facilities to transform certain types of textual and graphical input information are either already under construction or may be expected.

CSPSs are so far centralized systems which are mainly installed on large central computers. Frequently, they are accessed via telecommunications systems from teletype terminals. With the rapid developments of computer hardware, intelligent terminals, front-end computers and computer networks one should expect the development of CSPSs which allow for decentralized and distributed modeling and processing.

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FOOTNOTE TO CHAPTER 8

1. This chapter is based on E. Boissaye, R. Bürgisser, H. Kränzlin, S. Pellegrini, F. Rosenkranz "A new Corporate Modeling System (COMOS)", in: "Modellierungs-Software", S. Dickhoven ed., Gesellschaft für Mathematik und Datenverarbeitung, Bonn, June 1976, pp. 259-298 [3, 4].

Case Studies and Conclusions

GENERAL EXPERIENCES

PAST PROJECTS

Corporate modeling work or efforts within CIBA-GEIGY started already some eight to ten years ago. Much time was initially spent on a comparison of different modeling approaches, programming languages, and systems, some of it already spent for the CIBA Corporation before the merger of the two chemical companies CIBA and GEIGY took place in 1970 [30,45]. Two smaller corporate modeling projects were undertaken during this phase and both were abandoned, before any regular and practical application was possible.

The first pilot project dealt with the description of the activities and operations of a daughter company producing electronic equipment. This firm had to cope with severe problems mainly in the production area:

At times its inventory levels for finished and intermediate products were excessively high, in other periods a considerable order backlog was observed. Production was in batches and the process had several production stages. Since most of the intermediate products were used in several of the finished products, a description had to cope with a multiple echelon, facility, and assembly problem. The project was intended to, first, describe the operations of the firm in the areas of production, marketing and finance, and second, to show reasons for the inventory cycles observed together with possible policies to smooth the whole process. The project

was not initiated by the management of that particular daughter company, but by a central staff. The latter thought that it was possible to improve the quality of planning from the outside.

Since the phenomena observed at first sight seemed to resemble the examples described in Industrial Dynamics [14,30], the first model was coded using IBM's CSMP (Continuous Systems Modeling Program). Soon it became obvious that with this computer code, it was not easy to treat tables and matrices containing either measured or generated values of indexed model variables. These facilities are likey to be required for the type of problem described. The whole model was subsequently recoded in FORTRAN. It consisted of several hundred equations, approximately fifty of them being of the behavioral type. Some of these equations were fairly complex. Non-linear difference equations were encountered in the production segment, equations containing stochastic disturbances in the marketing segment.

The second model concentrated on the description and simulation of the markets of one of the operating divisions, the sales of approximately one hundred key products to these markets and the flow of funds and income margins connected with sales and distribution of the products on a worldwide basis. The project was partially carried out in parallel to the first one. It was abandoned before the construction of a production segment was begun.

In Chapter 2 we discussed four factors which have contributed to the failure of some corporate models. Certainly, in recent years model users and model builders have accumulated considerable experience and knowledge which help avoidance of the shortcomings mentioned above. But it seems that successful model building on one level of sophistication in a kind of dialectic process tends to create problems on other levels. This brings about that the same shortcomings may have to be overcome several times. In the following paragraphs, several CIBA-GEIGY models which were failures are briefly discussed.

INDUSTRIAL DYNAMICS MODEL

Although the Industrial Dynamics model managed to ex post reproduce some of the inventory cycles which had been observed in reality, it was never fully implemented. There were several distinct reasons for this result:

The analysis showed that the inventory cycles were mostly induced by

fluctuations of external demand and not internally generated, - a result which could be obtained independently from the model by a careful analysis of order time series and which could not be changed by something like an adaptive marketing strategy. Still one could have imagined that the model by its descriptive power could have served for planning purposes mainly in the production and manpower area.

It was then realized that not only did the pattern of external demand change rapidly, but also the firm itself with its production process and production mix. Since this first model had not been built in a very structured and modular fashion, it became clear that changing the very detailed model structure could not be achieved much faster than these structure changes actually occurred. Furthermore, the model variables, parameters and equations were not always understandable to the model users.

ECONOMETRIC MARKETING MODEL

The main reasons for the failure of the second more econometrically oriented model was the absence of user participation. After the user had roughly defined the intended use of the model, most of the data collection, model specification and testing was carried out by the model builders. During that time the potential model users had to occupy themselves with more pressing planning work which had arisen from changes in the planning procedures. It was under these circumstances not surprising to encounter a lack of identification of the user with the model when it came to decide on its implementation and regular use as well as financing. In retrospect one may still say that possibly a correct methodological approach had been taken. It should also be mentioned that the project made the development of a number of modules and data base utilities possible which are still used with the currently implemented systems. But the failure to close the "model-manager interface" did not allow the implementation of an otherwise probably feasible approach.

As a reaction to a method oriented modeling approach one may currently often observe a subjectivist approach to model building which sometimes leads to an overestimation of organizational and behavioral aspects. The following case study is intended to illustrate the pitfalls connected with this approach:

DECISION CALCULUS MODEL

In a pioneering article appearing in 1970 Little described a number of criteria, a management science model should fulfil if it is to be used as a tool for management decision making [31,32]. These criteria mostly apply to a systematic construction of models which, first, rely on a number of "objective facts" known about these phenomena(e.g. market-share, sales price of a product), secondly, exploit the a priori knowledge managers have about a phenomena (e.g. distributed lag effects between sales and advertising, relative efficiency of different ways of using an advertising medium) as far as possible. A number of cross checks are used to test whether the user's a priori knowledge is compatible with the objective facts before the model itself is subjectively parametrized by its user. Little demonstrated his approach using a marketing example which - with minor modifications - was used for sales and profit planning for consumer products in one of the CIBA-GEIGY subsidiary companies. The sales effects of detailing were described by a few structural equations which took memory and forgetting effects as well as the effectiveness of different detailing positions or positions on a leader list into consideration. Given a detailing budget for several periods and subjectively parametrized models for several products a heuristic procedure was used to determine a profit optimal detailing allocation with respect to products and budgeting periods. The interactive system was constructed in cooperation with the users by an internal management science group and a competent external consultant. It was used on a regular basis for about two years before it was abandoned.

There were several reasons to this outcome.

1. The model was easy to conceive and operate and with time the users learned it in detail. It was not possible to prove that a decomposed estimation of the phenomena resulted in a more accurate estimate for the total marketing process. For some time the sales forecasting segment was used as a kind of management game, then the users directly fed their estimates of its response into the more operations research oriented allocation heuristics until also the use of this segment was discontinued.
2. A validation of the model by ex ante forecasting was found to be extremely difficult. New products for which no objective facts were available were frequently introduced into the market and had to be

budgeted as well. Also there was always special justification for deviations from the detailing plan the model had produced. However, in contrast to the user's a priori knowledge and specifications some tests gave indications that the model overestimated the effects of detailing on sales and that also the time pattern generated by the model did not closely correspond to what was observed in reality.

3. The same market had been modeled for some time using econometric distributed lag models. Whereas the above described Decision Calculus model only dealt with detailing, because the users thought this to be the decisive medium under all circumstances, the econometric models indicated a lower effectivity of memory detailing and a marked influence of other types of advertising and competitive behavior. Also a better model fit was obtained in these econometric investigations if a decay effect in detailing efficiency was assumed, i.e., less weight was given to memory advertising. Direct field research in other marketing regions has later supported this result.

In total it seems as if the latter type of models, although they were definitively less user oriented and relied much less on the user's conception of the whole marketing process, gave a better picture of reality than the particular decision calculus model described.

The example also shows that not only learning on the model builders', but also on the users' side is necessary. The original approach fulfilled most of the organization, behavioral and psychological criteria discussed especially in chapter 2, but obviously had shortcomings in the estimation and validation steps of the modeling procedure.

CONCLUSIONS

The previously described failures to construct CSPMs at CIBA-GEIGY supplied valuable experiences to the model builders with respect to the type of project-management, methodology, and techniques to be employed with a corporate modeling project. At the time the first two projects had ended, an elementary, but robust and workable first version of a CSPS (COMOS I) was available. With the commitment of a third user it was possible within two months to construct a sales extrapolation model for one of the operating divisions. At first it simply substituted the manual calculation of "What if?" planning alternatives, the first objective was often

merely to automize the calculation of planning alternatives which previously had taken up to several man-months for each alternative. In this initial phase, the models were able to supply the user with a great number of more timely, consistent, and accurate planning alternatives. Such a "bread and butter" approach, starting with straight-forward, rather simple deterministic simulations, gradually turning to more complex applications, results in an identification of the user with "his" models. On the other hand "errors of the third type" are avoided, i.e., the approach prevents the model builders from constructing good models for the wrong problem. The models which are presently implemented were coded in an extremely modular fashion in order to allow a fast and flexible generation of alternative model structures. Indeed, different "What if?" or "What to do to achieve?" investigations sometimes require changes in the model structure and in the method of solution from one computer experiment to another.

Again it should be stressed that especially the last requirements call for a flexible and modular CSPS. If a CSPM were only to be used within the traditional planning process answering a prescribed number of questions in regular time intervals, ready made models or tailor made models calling on fixed model blocks performing specific modeling tasks would also solve the problem (Grinyer, Wooller [19]). A planning process that adapts quickly to unforeseen external as well as internal qualitative as well as quantitative changes must be supported by CSPMs which are able to adapt quickly to such changes (viz. Ansoff [2]). The models presently either being implemented or constructed at CIBA-GEIGY should perhaps not be called CSPMs in a strict sense, because they are either not far enough developed to describe the firm's activities equally well in the areas of finance, marketing, and production, or they were developed to solve specific planning problems in a functional or organizational area with no initial intention to describe other areas as well. However, one may observe a tendency to extend the models to areas initially not foreseen, or to close gaps between models in different areas. As a consequence, the model builder's attention has shifted from mainly methodological and computational problems to questions of model and data base compatibility and integration as well as goal formulation.

Something like a CIBA-GEIGY master model does not exist. Instead a family of models for different users having different objectives was constructed. An identical data base design and the same methodology was used for these models and this allows their linkage and integration. Especially

the corporate financial models are fully integrated into the either rolling short- or middle range planning procedure, but they may also be used for ad hoc investigations. Some of the marketing oriented models were intended to support short or long range ad hoc studies, but may also be used regularily.

Some of these corporate modeling applications will be described in the following sections before a more general summary is given and conclusions are drawn.

ORGANIZATION

The corporate modeling case studies described below are in a sense representative, but not exhaustive descriptions of the corporate modeling work undertaken at CIBA-GEIGY.

Most of the models have been constructed by members of the central Operations Research group. Organizationally this group is within the central CIBA- GEIGY controller's function in parallel with the data processing department. Group members worked as internal consultants for divisional and functional departments and had to do their own acquisition and marketing. The modeling projects were undertaken by teams which normally had to be fully financed by the user departments. The first two corporate modeling projects, which in fact also failed, were an exception to this rule. Project proposals, and especially the specification of intended model use, time schedules and estimates of costs and benefits were formulated by both the users and model builders. Financial benefits other than due to the reduction of clerical work were usually not quantified. The "sponsors" of the project were the heads of control, marketing or planning of the corporation, divisions or subsidiary companies. The users in a technical sense were in most cases staff personnel in the user departments. Depending on the type of model and educational background either members of the user or the Operations Research department acted as model "chauffeurs".

FINANCE

Financial corporate models have been built for the CIBA-GEIGY Corporation as a whole, for three divisions on a world wide basis, for one group

company, and one division within another group company. The corporation model has already been used for four of the yearly middle range planning cycles whereas the other implemented models have been used for three planning cycles. Originally the models worked on a yearly time base with a time horizon of ten years. However, in most investigations only three years of this planning horizon were evaluated. Some models have also been used for short term budgeting purposes on a quarterly time base. The corporation model is only based upon monetary values. The divisional model within one group company is largely used for income margin simulations on a quarterly basis and possesses a database disaggregated down to the level of single products with historical measurements as well as planned and budgeted values of the model variables. A combination of subjective parametrization, statistical estimation and forecasting methods are used for the latter model, whereas the other financial models are subjectively parametrized. This is partially due to the merger of the CIBA and GEIGY Corporations in late 1970. The control and planning procedure of the two firms differed considerably and new procedures had to be developed. Since only few historical data were thus available, calculations and data extrapolations heavily relied on the practicioner methods described in chapter 6. This will probably change when more historical measurements become available.

The financial models were constructed for the central control function of the company or planning and control functions within the divisions. The divisional models are among others used to generate base plan solutions to be fed into the corporation model.

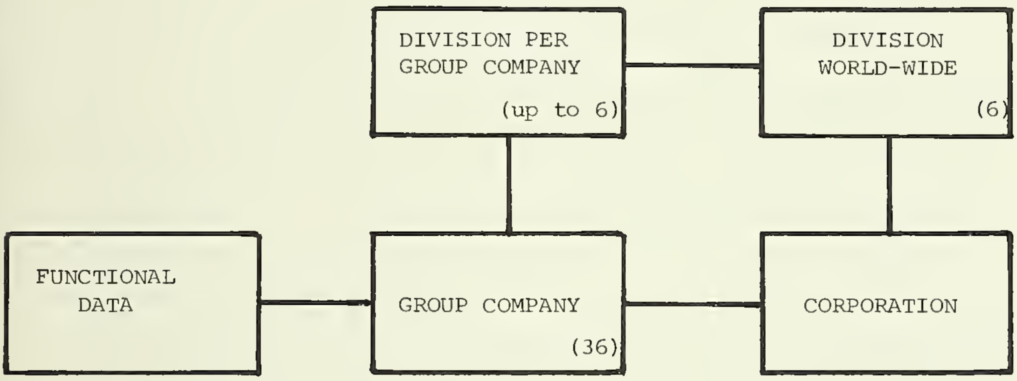
The corporation model is presently the largest and furthest developed operating financial corporate model at CIBA-GEIGY. A first version was developed with the relatively small effort of some nine man-months. To characterize the financial models, mainly the corporation model will be subsequently described.

INTENDED USE

The model was intended to allow simulations on the divisional, functional, group company, and corporation level (viz. figure 9.1). The model input and output are mainly in the form of divisional contribution statements, income statements, and balance sheets of the group companies as well as of the group as a whole, and tables with financial key figures.

CIBA-GEIGY is subdivided into six divisions which operate on a world wide basis with more than 60 group-companies. Because the major 36 planning companies of those have to be dealt with in the model, it became necessary that model calculations had to be carried out in about 250 tables or matrices of the order 50x100. The model was conceptually understood to be a tool for middle- to long-range computerized planning, intuitive forecasting, and general exploration purposes.

Figure 9.1. Levels of aggregation for financial models



More specifically the objectives of the model were:

1. To aggregate the various data in order to obtain an overall view of the group, divisions or group-companies by means of income statements, balance sheets, and financial key figures.
2. To evaluate critical factors and to quantify the influence that uncertain exogenous variables, such as raw material prices, currency parities, and labor costs have on the contribution of the different organizational units or the profit of the company as a whole.
3. Essentially the same analysis should be feasible with respect to decision variables of the firm, i.e. to simulate the effects of quantitative and qualitative policies, such as sales prices, large investments, and acquisitions.
4. The user should be able to generate model solutions especially on the division and subsidiary company level, once targets and relations to allow a disaggregation have been defined and supplied on the corporation level.
5. The model input should be largely based on the firm's effective, budgeted or planned values of the model variables. The model output

should be compatible with the information needed for the firm's established planning and control procedures.

MODEL DATA

Two types of input data were distinguished: Those which were available from the firm's information systems and those which were prescribed or subjectively estimated and supplied by the model user. The historical, effective and the prospective planned and budgeted values of the model variables belong to the first type of data. They were mainly given on the sub-divisional and subsidiary company level. Data of the second type comprise subjective estimates of parameters or exogenous variables, target values of the endogenous variables, and values of the decision variables. Examples were coupling parameters between sales and variable costs, liabilities and receivables, exchange rates, sales or profit target values and sales prices, respectively.

Model data and variables were defined with respect to several levels of aggregation (viz. Figure 9.1). Changes in variables on a lower level of aggregation in general cause changes in variables on higher levels of aggregation and vice versa. Variable names had therefore to be chosen in such a way that tree calculations may be carried out effectively.

EQUATIONS

The number and type of the model equations varied from experiment to experiment. In the case that a simulation was carried out on the level of a division per subsidiary company, and if the results on the levels of the subsidiary company and corporation were also of interest, several thousand equations had to be evaluated. More than 90% of them were bookkeeping identities and definitions. The predominant number of equations was of the linear, deterministic and recursive types. An example would be equations to describe the level of liquid funds and liabilities on the one hand and the flow of expenses on the other. Figure 9.2 hosws a GESIFLOW-graph related to a deterministic "What if?" simulation of sales changes at the subsidiary company level. It is seen that six model variables interact.

Similar reductions had to be used to deal with parity changes and intercompany sales.

SIMULATIONS

All three types of questions have been answered with the model. The latter ones were either answered analytically or numerically mainly by backward induction for exactly determined recursive models in which the target variables are treated like exogenous variables. However, most often the user formulated "What if?" questions, requiring a completely recursive, linear or non-linear model structure. Very often these consisted only of isolated changes in the planning database and consolidations. Such calculations were typically specified in interactive mode. Goal programming solutions were generated in one instance, deterministic response surfaces were established and graphically presented in another investigation. But such techniques are not used on a regular basis yet.

MODEL TESTS AND VALIDATION

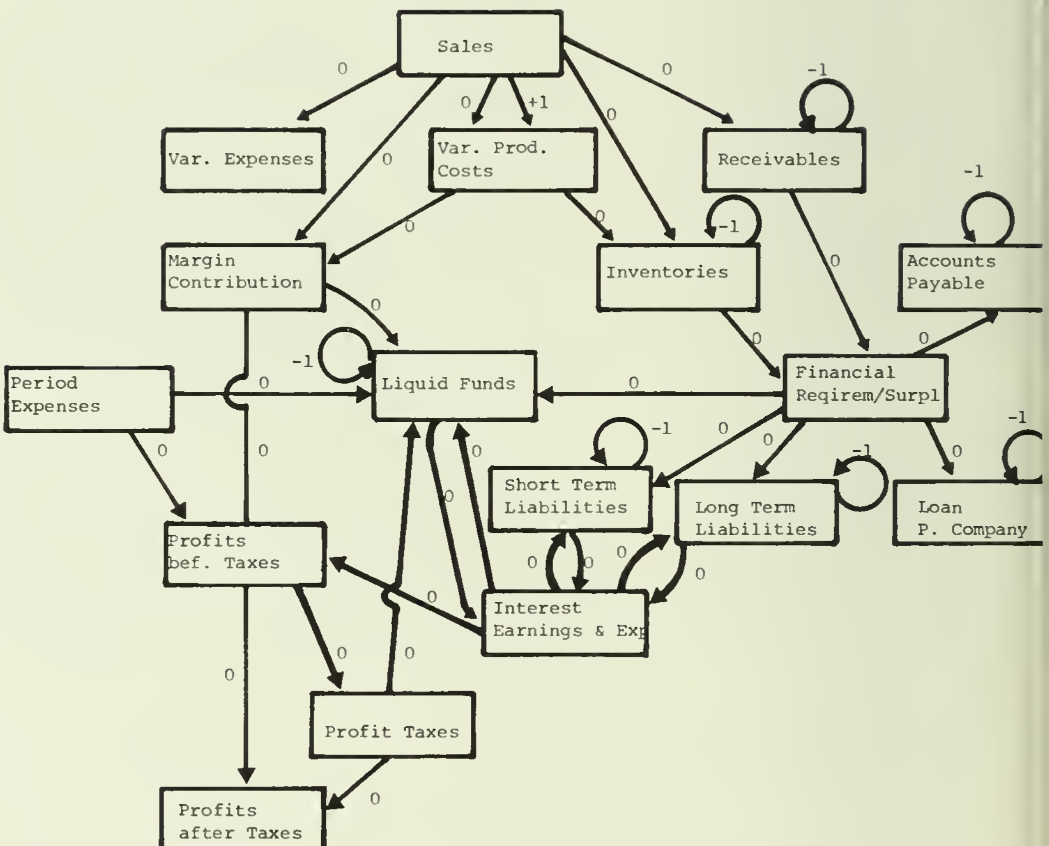
Since no sufficient and comparable historical values of the model variables were available, there was no other possibility than to test the consistency of the model output with respect to the results of a planning alternative which previously had been calculated manually.

IMPLEMENTATION AND EXPERIMENTATION

Immediately upon the first operational version of the model being completed, it became a valuable tool for the company's annual rolling three year planning. Users tried especially to quantify possible consequences of such harrassing problems as were caused by instable currency parities and the increase and expected changes in raw material prices. Also the effects of different pricing policies were tested.

Whereas the users specified their hypotheses and assumptions, the necessary coding and model runs were initially carried out by the model builders in the central Operations Research department and presented to the user. In order to bring the user even closer to the model and to liberate the model builders from a, in principle, largely unnecessary service function subsequently modules were programmed that allowed changing and editing

Figure 9.2. GESIFLO-graph "What if?" question



the model database as well as specifying standard model runs in interactive mode (TSO) using a screen. Members of the planning and control functions were trained in the use of the model and model builder support is only necessary for the simulation of unforeseen events and an adaption of the model to changes in the planning process.

MARKETING

CONSUMER PRODUCTS

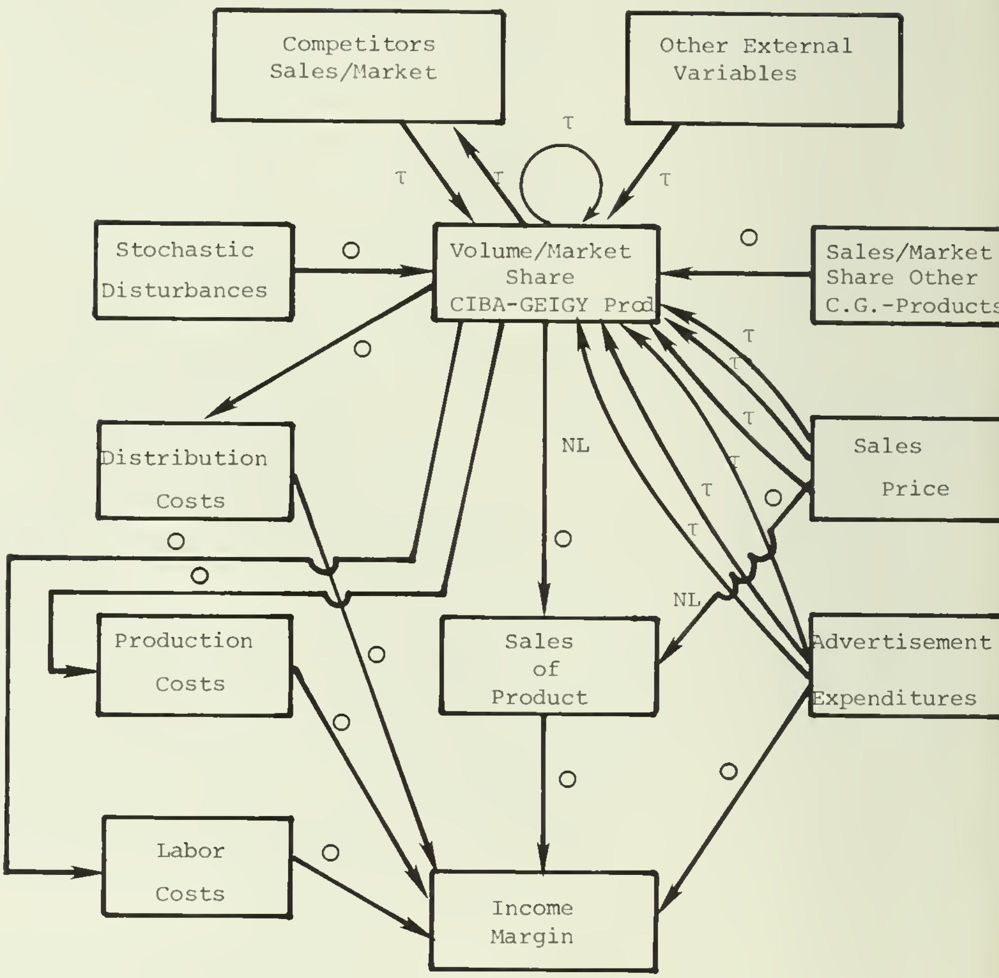
With the financially oriented models little weight was put on the numerical estimation of model parameters. So far only expert guesses have been used. This will probably change to some extent as more historical measurements of the model variables become available and some of the models describe more accurately the firm's relationship to its surroundings, e.g., on the capital, personnel and raw material markets.

Corporate modeling activities in the marketing area have developed in exactly the opposite direction: Commencing with only a few stochastic linear or non-linear model equations, they were supplemented by a great number of mainly linear deterministic model equations. They describe the financial and production segment. The graph shown in Figure 9.3 gives an impression of the variables and relations which were dealt with in one of the operating models. The general structure of a single product model is shown.

It should be noted that Figure 9.3 indicates complicated relations in the marketing area which usually were not dealt with simultaneously. Some of the experiences obtained with these and earlier models have already been extensively described in the literature [46,48].

The graph in Figure 9.3 expresses only conjunctive relations between the model variables, i.e. they have all to be taken into consideration whenever the models are solved. In principle the model comprises two segments. One of them consists of an econometric marketing model, the other is essentially a deterministic financial model. Only lead-times or time-lags are indicated on the arcs of the graph. It would be easy to specify the transmittances of the arcs for the financial segment. Because the equations of this segment are mostly linear identities, most of the transmittances would

Figure 9.3. Graph for corporate marketing model



be equal to one. However, the transmittances have to be determined by statistical analysis for the marketing segment, because the time-shifts denoted by τ may vary from model to model. The loop between "competitors' sales" and "volume" expresses that these variables may interact. The self-loop at node "volume" signifies that sometimes autoregressive models have to be used. The time-shift τ may attain positive values for some arcs, thus indicating lead times. For the arcs between "sales price", "advertising expenditures" and "volume" they are negative, indicating the time-lags. Multiple arcs between the same nodes indicate distributed lag effects. Heavy use of econometric estimation, specification and validation techniques was made for the marketing segment. In the financial segment mainly

bookkeeping identities were evaluated.

The steps of the model design procedure may be described as follows:

Intended Use

The models were intended to serve as tools for forecasting, controlling and budgeting sales and income margins of single or groups of consumer products over a short to mid-term time horizon. The basic time unit of the models was typically a month or quarter. More specifically the objectives of the models were

1. to estimate statistically advertising and price coefficients or elasticities and thereby to quantify the effects which the decision variables of the firm have on sales and market-share of the products or products-groups. The estimated coefficients and their variance-covariance matrix should allow hypothesis testing with respect to the absolute and relative profitability of the different advertising media. Such hypotheses may concern single products or comparisons of the effectivity of advertising between different products and product groups. Statistically significant results should give indications for a better distribution of advertising expenditures among the different media and products or product groups. In one investigation marketing managers were also interested, in the time dependence of the advertising effectiveness. More accurately: They wanted to know whether the advertising effectiveness depended on the age of a product and whether it was possible to give indications of a better distribution of advertising expenditures over the life cycle of the products. The life cycle of the products typically vary between four and ten years.
2. In order to enable management to budget product sales and marginal income more accurately, it should be possible to generate prospective predictions of sales with given values of the decision variables. The effects of variations in the model parameters or exogenous variables on income margins should be quantifiable by simulation.
3. The models should allow a comparison of historical,budgeted, forecasted and effective values of the model variables. This should give indications about the predictive performance of the models and render an analysis of the reasons for deviations between budgeted and effective values possible.

The intended use and objectives of the models implied that the user was able to pose "no external decision" questions regarding the past and present of the marketing system's development and to pose "What if?" questions concerning the future development of the system. Optimizing or "What to do to achieve?" investigations have not yet been carried out. It must be understood that the estimated model parameters are only valid with respect to small variations in the values of the decision variables. Since most of the model equations were either linear or intrinsically linear, an optimization would either effect great changes in the levels of the advertising and price variables or necessitate the formulation of additional constraints like upper and lower bounds.

Data

The database for the model contained both cross-sectional and time series data. Four kinds of data were distinguished: Full sample data which are manually collected within the firm, an example being advertisement expenditures measured in impulses or values, data from the firm's information systems ,such as sales by volume and value, sales prices and different cost elements, panel data obtained from external sources describing the market-share of own and competitor-products, competitors advertisement expenditures and sales. Finally, some model data had to be estimated subjectively by the model user such as transformation factors between advertisement impulses and expenditures.

Equations

Nearly all the types of model equations which have been described especially in chapters 4 to 6 have been encountered. However, the models so far did not conatin any inequalities or boundary conditions. The financial segment of the models typically consisted of identities and definitions with some technological equations to relate costs and sales. These equations were without exception deterministic linear and did not even contain any lagged endogenous or predetermined variables. The marketing segment of the models was mostly described by a set of linear single equation regression models as they have been discussed in chapter 6. Descriptive smoothing and forecasting techniques as described in chapter 6 were used together with endogenous and generalized trend models. However, in the predominant number

of cases, explicative models were employed to describe sales by volume and value of market-share as function of the advertising expenditures, and prices and other variables which are related to the firms competitors and surroundings. Such models were in general of the distributed lag type. In the predominant number of cases they were linear in both the model variables and model parameters. In a number of instances distributed lag models both non-linear in the model parameters and model variables and also linear simultaneous equation models were formulated and applied. Very rarely have models comprising more than two simultaneous equations been employed so far.

Non-linear single equation models usually correspond to the trend models and generalized trend models that have been described in chapter 6. Apart from this special application, hypotheses concerning the time dependent effectiveness of advertising were expressed in non-linear models. The following simple example may illustrate such applications:

With the investigations mentioned, one could often observe that advertising expenditures attained their largest values with or shortly after the introduction of the consumer products into the market. Thereafter, they exhibited a falling trend. It was therefore plausible to distinguish between a kind of initial advertising and a mere memory advertising. Discussions and an analysis revealed that the marketing managers who were responsible for the allocation of advertising efforts had intuitively taken care of two marketing phenomena: They had assumed a law of decreasing return to scale with time (viz. Little, Lodish[32], Benjamin, Maitland [5]) and memory effects on the consumers side (viz. Vidale, Wolfe [57], Rosenkranz [46]). These assumptions may be expressed in an econometric model. Assume, for the sake of simplicity, that only one kind of advertising, denoted by x_t, is used and that s_t represents sales of the product in periods $t = [1,n]$. In a first approximation one might ask sales to be directly proportional to a proxy variable y_t according to

$$(9.1) \qquad s_t = \delta \cdot y_t$$

The variable y_t could correspond to the number of customers which at time t are conscious of the fact that the product is able to fulfil certain needs, δ would be a proportionality constant. This consumer consiousness may now on one side be increased by advertising. On the other side it may decrease because consumers tend to forget the advertising impulses they have been exposed to. Memory advertising is assumed to count-

eract such effects. In addition a time dependence of the effectivness of sales has to be considered. If advertising does not change qualitatively over time, one may often assume that, due to wearing out effects, its effectiveness decreases with time. With these assumptions it is possible to describe both phenomena with e. g. the first order model

$$y_t = y_{t-1} + \alpha_t \cdot \sum_{\tau \geq 0} \beta_\tau \cdot x_{t-\tau} - \gamma \cdot y_{t-1} + u_t \ ; \ t = [1,n] \tag{9.2}$$

The factor α_t expresses the decrease of effectiveness with time. In a number of investigations the following expression was used:

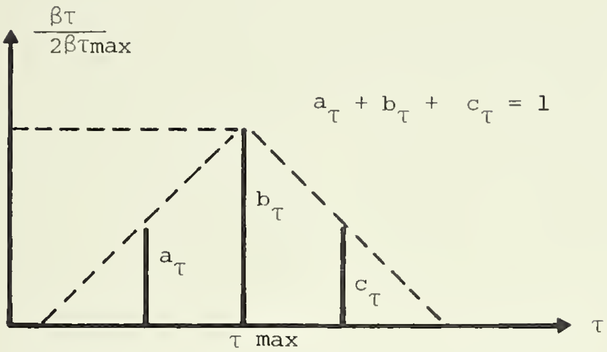
$$\alpha_t = \exp \{- \frac{(t-1) \cdot \ln 2}{\tau_{1/2}} \} . \tag{9.3}$$

The constant $\tau_{1/2}$ expresses the half- advertising effectiveness, i.e. the time after which a unit impulse results in only half the sales effect it had at t=1. Also the other variables in eq. (9.2) deserve a short explanation: The parameter γ corresponds to a first order forgetting constant, u_t denotes a stochastic disturbances whereas the sum $\sum_\tau \beta_\tau x_{t-\tau}$ expresses a distributed lag effect. In eq. (9.2) it has been assumed that not only advertising in period t has effects on y_t and therefore sales s_t, but also advertising in previous periods $(t-\tau)<t, \tau \geq 0$. The weighting factors β_τ usually describe what is called a distribution of lag coefficients. It is clearly seen that eq. (9.2) is non-linear in the model parameters and model variables. A substitution of eq.(9.1)in eq. (9.2) at once reveals that the latter may be directly used to describe sales s_t as a function of the advertising expenditures.

It has been noted before that practically only distributed lag models were used to describe carry-over effects between sales and advertising with the two projects mentioned. Such models usually require a lot of a priori specification on the user's side. The number of available measurements on one side and the estimation properties of a model on the other effect that in most practical applications only a few of the lag coefficients β_τ in eq. (9.2) were estimated. Together with a hypothesis regarding the distribution of lag coefficients these then permit the calculation of the remaining coefficients. Normally the distribution of the lag coefficients is assumed to be normalized, i.e. the sum of all β_τ should result in a finite value. Figures 9.4 exhibits one of the lag distributions that has been applied in the investigations described.

The inverted V or triangular lag distribution requires in the simplest

Figure 9.4. Inverted V-lag distribution



case that the user supplies three weighting factors a_τ, b_τ and c_τ subjectively for given values of τ. These then serve in a calculation of one single transformed series $\bar{x}_{t-\tau max}$ in eq. (9.2). Only one coefficient $\bar{\beta}_\tau$ then has to be estimated and the remaining coefficients may be calculated from the weight distribution shown in Figure 9.4. If, alternatively, the a_τ, b_τ and c_τ are not fixed a priori, three coefficients are estimated and allow the calculations of the remaining ones. The advantage of the distribution clearly is its simplicity and flexibility, since different weight distributions may be calculated for different advertisement media. Its disadvantage is that it requires many a priori assumptions (viz. De Leeuw [11], Rosenkranz [46]).As a result of these limitations, we have also used polynomial lag distributions (viz. Drymes et al [12,13], Almon [1], Cooper [9], Kugler [28], Frost [15], Godfrey, Poskitt [16])and infinite geometric distributions . Such lag distributions have been used by Montgomery and Silk [39] for a similar study. Originally, their econometric application dates back to Koyck (viz. Koyck [27], Wallis [59], Dhrymes, Klein, Steiglitz [12], Liviatan [33], Scadding [51]). It should be noted that although such a distribution does not force the user to arbitrary truncate his lag distribution as with the finite distributions, this advantage in many applications is paid for by estimaticn problems and a loss of flexibility.

Estimation, Solution, and Simulation

COMOS II provides the ordinary least squares metods (OLS), the two stage least square method (2SLQ) and the Levenberg-Marquardt algorithm for non-linear estimation. In the predominant number of cases ordinary linear least squares (OLS) was employed. A user may either directly specify the

the above mentioned lag distributions or employ COMOS statements to generate other distributions. The estimated coefficients and their empirical variance-covariance matrix were employed to generate point or interval predictions, once the values of the exogenous and decision variables had been specified. Exogenous variables were either forecasted themselves or, especially in the financial segment of the models, extrapolated or interpolated with the simple practicioner models described in chapter 6. The solution of the models so far was straight forward, because they were mostly linear and recursive. Nonlinear model equations only contained predetermined, exogenous and decision variables as explanatory variables. A Monte Carlo simulation with repeated estimations was used in one investigation to test the effects that time dependent measurement errors in the panel data employed had on the estimates of the model parameters and their variance-covariance matrix. Serious deviations in the absolute values of the coefficients and the variance-covariance matrix were detected. They suggested that model forecasts should sometimes be handled with extreme caution. However, it was also established by Monte Carlo simulation that an ordinal ranking of the regression coefficients was not much effected by the measurement errors.

Testing and Validation

Heavy use of specification testing was made in order to establish the marketing segment of the models. The tests employed have been described in chapter 6 and include the Durbin periodogram test, the Durbin h-test, the Farrar-Glauber tests and the Cochran-Orcutt procedure to sometimes cope with models containing predetermined variables. Wold's Janus coefficient or Theil's inequality coefficient was used to test the accuracy of retrospective model predictions. The performance of the econometric models was compared with the forecasts obtained from naive or purely descriptive forecasting models. Prospective predictions were supplied to the model users.

Results and Implementation

Mainly five types of results were obtained from the analysis of sales or market share as a function of selling prices and advertising:

1. Results concerning the effectiveness of different advertising media and price effects.

2. Results concerning single products.
3. Modeling outcomes which were of interest with respect to the market segments and product groups to which the individual products belonged.
4. Comparison of the predictive accuracy of alternative models.
5. Conclusiȯns about the use of the data, models and methodology described for decision making.

Such results and their interpretation mainly rest on the outcomes of various statistical identification, confidence, specification and validation tests, once they were found to be plausible and compatible with the users knowledge and intentions.

The explicative distributed lag models used clearly assume a kind of investment effect of advertising: Expenditures or cash-outflows cause cash-inflows which may be lagged and distributed over time. Hence, a discussion of the phenomena has to deal with both, the time effects 'advertisement investments' have and their absolute or relative magnitude.

The lag distributions used in the investigations were usually specified after a preliminary correlation analysis had been carried out [46]. Although such a specification is not much more than a heuristic procedure, it has proven to be effective in practical applications. Similar experiences were obtained by Almon [1, p. 181] in another context.

The specification procedure works roughly as follows: Based on the a priori knowledge he possesses, the user specifies lower and upper limits of the lags he expects to appear significantly in a lag distribution. For most of the investigations using monthly data this was $0 \leq \tau \leq 8$ (months). Within these limits all coefficients $r(s_t, x_{it}, \tau)$ of the lagged correlation between sales or differenced sales s_t and the m explanatory variables or suitably differenced variȧnces, say x_{it} ; $i = [1,m]$, were calculated together with the appropriate values $t(s_t, x_{it}, \tau, n)$ of their t-distribution (viz. van der Waedern [56]). The constant n denotes the number of measurement used for the calculation of r. One has the location of the mode

$$(9.4) \qquad t(s_t, x_{it}, \tau, n) = r(s_t, X_{it}, \tau) \cdot \left(\frac{n-\tau-2}{1-r^2}\right)^{1/2}$$

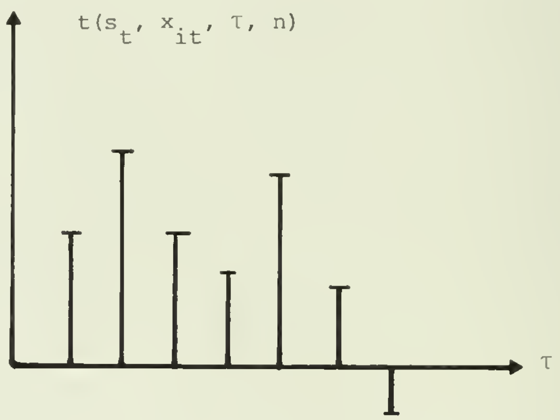
and using

$$(9.5) \qquad t(s_t, x_{it}, \tau_{max}, n) = \max_{0 \leq \tau \leq 8} \left\{ t(s_t, x_i, \tau, n) \right\}$$

of the lag distribution was determined empirically taking also the number of degrees of freedom of the distribution into consideration. The general

the pattern of $t(s_t, x_{it}, \tau, n)$ as a function of τ then often suggested the type of lag distribution to be used. Frequently $t(s_t, x_{it}, \tau, n)$ was not a unimodal function of τ. An example is shown in Figure 9.5. Such difficulties were overcome either by specifying different lag distributions and comparing the results of the alternative estimations or by performing the same analysis with partial correlation coefficients. In a number of instances also a direct estimation of some lag coefficients provided indications as to which lag distribution should be used.

Figure 9.5. Distribution of t-values of cross-correlation coefficients



A comparison of the lag distributions obtained for different media and a great many products showed that it was reasonable to distinguish different delays and time patterns for the advertisement media. Other investigations revealed that empirical evidence supported the assumption of a finite halflife of advertisement effectiveness as has been expressed in the simplified model eqns. (9.2 - 9.3).

It was possible to perform hypotheses testing with a large number of the linear or intrinsicly linear models from the investigations mentioned. These models had passed the specification tests available in COMOS to check whether the assumptions of the general linear model were fulfilled. Denote with α the error probability that a single zero hypothesis H_0 may be rejected. Using the t-distribution one may then construct confidence intervals for hypotheses expressed as linear combinations of the model parameters, say,

(9.6) β_ν, $\nu = [1, \nu^*]$, i.e.

$$H_0 : f(\beta_\nu) \equiv \sum_{\nu=1}^{\nu^*} c_\nu \beta_\nu = k,$$

where the c_ν and k are user supplied constants. Alternatively one may test zero hypotheses involving assumptions on several parameters in one model or groups of parameters in different models using appropriate values of the F-distribution.

Based on the assumptions mentioned, these tests allow one to tentatively answer such questions as

1. Did the sales price or an advertising medium significantly influence sales or market share?
2. Did an investment in advertising cause cash inflows in the same order of magnitude?
3. Was there a significant difference in the effectivity of advertising (coefficients, elasticities) between different media?
4. Was the sales effect of advertising short or long term?
5. Was there a significant difference in the effectivity of sales between different time periods or different products?
6. Were effective sales compatible with ex ante or ex post predictions generated by a certain model?

In about fifty percent of the investigations, results were obtained that formally answered at least one of the questions given above. It should be noted that not only parametric tests, like the ones mentioned above, have been performed, but that in a number of instances also non-parametric hypotheses testing was carried out (Rosenkranz [46]). In contrast to the financial models described above, the users of the statistical models were very much dependent on the interpretation the modeling teams attributed to the statistical results. So far it is difficult to tell exactly how often and how strongly the modeling results have influenced actual decision making.

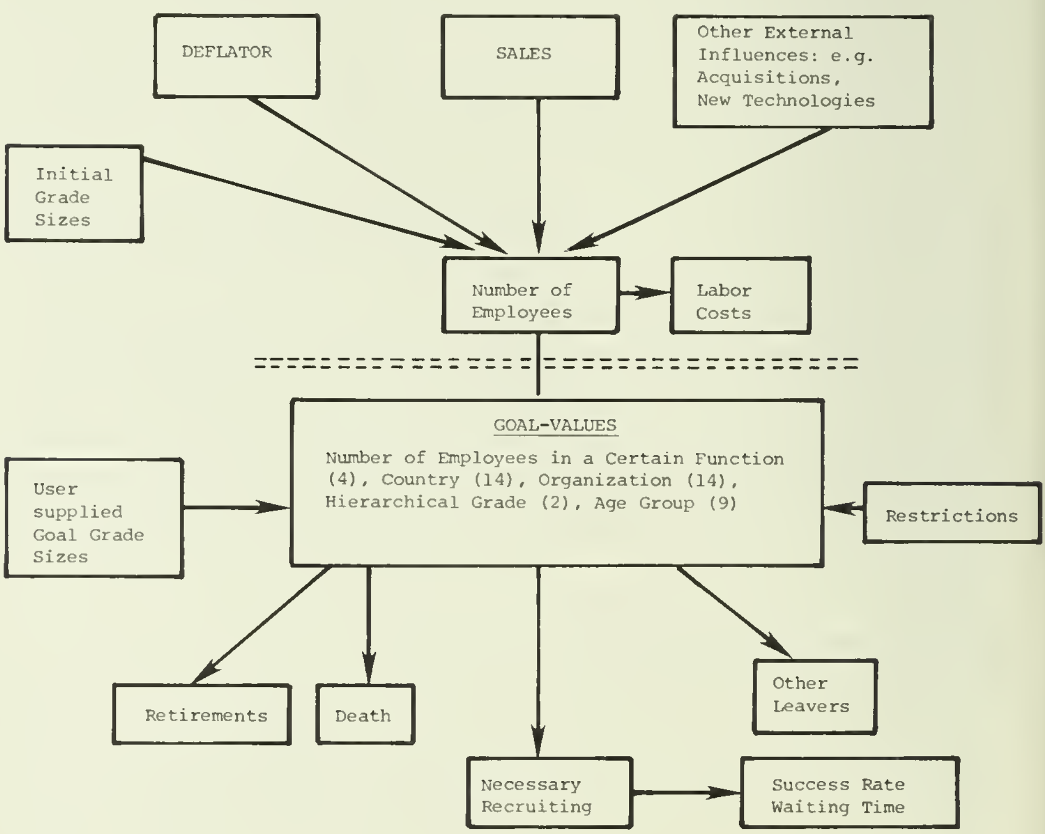
MANPOWER PLANNING (VIZ. ROSENKRANZ, PETER [50])

A CIBA-GEIGY manpower planning model may be connected to the corporate financial model described before. Figure 9.6 describes its main aspects. The linkage is optional and may be accomplished by feeding sales values and labor costs into the database of the manpower planning model. Such external data may be employed in the formulation of target grade sizes for different manpower categories.

Objectives

The model was intended to serve as an instrument for long range manpower planning on a world-wide basis. The planning horizon was up to ten years on a yearly time base. The model shows the effects of different business expansion or contraction rates, retirement, promotion, hiring and leaving rates on the demand for certain categories of employees and their age distribution. It distinguishes approximately 700 populations which are subdivided into two hierarchical grades, fourteen geographical regions, and four types of activity.

Figure 9.6. Structure of manpower planning model



Either the user supplies target grade sizes as input or they may be calculated by a COMOS model which e. g. relates deflated sales and the number of employees. These may again be decomposed into different categories using historical percentages and input specifications about foreseen changes. With given targets the model determines the necessary recruitments or promotions to attain or minimize deviations from targets.

Data

The database of the model contains data from the firms information systems or financial models, such as age distributions, number of employees, labor costs and sales. Other data were collected manually, examples being national pensioning data, death and leaving rates and historical data on promotion and hiring. For comparison purposes some time series on the development of the labor force and deflated sales of the main competitors were collected and analyzed from published sources [50].

Equations

The basic model structure consisted of a controlled markov-chain as has been explicitely described by Bartholomew [3, pp. 55-94]. Eq. (9.7)

(9.7)
$$y_{j(t+1)} = \sum_{i=1}^{n} p_{ij} \cdot y_{it} + \Theta_{jt}$$

describes the expected number of employees who are in grade j = [1,n] at time (t+1). This number may recursively be calculated from given initial populations y_{io}, probabilities p_{ij} for the uncontrolled transitions between two grades i and j in a planning period and recruitment and promotion decisions Θ_{jt}. Target values were formulated for sums of the $y_{j(t+1)}$, say

(9.8)
$$yT_{k(t+1)} = \sum_{i=i_1}^{i_2} y_{i(t+1)}$$

The y_{jt} and Θ_{jt} were generally restricted to nonegative values. Additional equality restrictions on the Θ_{jt} resulted from the formulation of recruitment and promotion distributions. These restrictions permitted the analytical determination of the Θ_{jt} in eq. (9.7) as a function of given grade sizes y_{io} and target values $yT_{k(t+1)}$. If desired, the model also calculated the variances and covariances of the grade sizes.

The target values were in most cases given as input. In some experi-

ments they were determined from a ratio

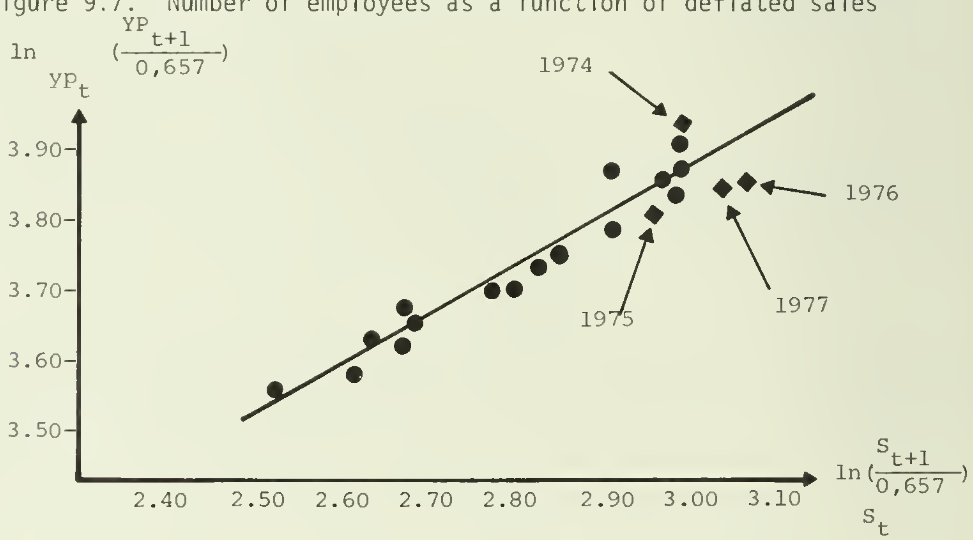
$$yT_{k(t+1)} = \alpha_k \cdot yP_{t+1} , \tag{9.8}$$

where yP_t is the total number of employees and α_k a factor which was determined as average from historical data. Equations like

$$yP_{t+1} = a_o \cdot yP_t^{\rho} \cdot \left(\frac{S_{t+1}}{S_t^{\rho}} \right)^{a_1} , \tag{9.9}$$

where a_o, a_1, and ρ are regression coefficients and S_t deflated sales, were used to link the development of yP_{t+1} to an extrapolation or plan for the S_{t+1} (viz. Rosenkranz, Peter [50], McClean [36]). Figure 9.7 gives an impression of the accuracy one may expect from such a relation. Clearly the last recession has at least temporarily changed the historical pattern and the coefficients in eq. (9.9) may only be used as 'yardsticks' for

Figure 9.7. Number of employees as a function of deflated sales [1]



CIBA-GEIGY 1957 - 1973 (estimated)

extrapolations. To test the effects of errors in eq. (9.9) in a number of model runs the number of employees was linked to stochastic extrapolations of deflated sales.

In addition to the equations described, other relations were employed to express mean success rates and promotion waiting times for the grades

and identities for consolidation purposes [50].

Estimation, Solution and Simulation

Econometric estimation methods (OLS and Cochran-Orcutt procedure) were employed to determine the parameters in eq. (9.9). Transition probabilities for the markov-chain model eq. (9.7) were estimated from manually collected data outside the model. In most cases only expected model solutions were calculated.

Testing and Validation

The face validity of the model was established with the user. Ex ante forecasts for three years were found to be compatible with the measurements.

Results and Implementation

The model showed for several populations and areas discrepancies between manpower requirements and actual or forecasted populations.

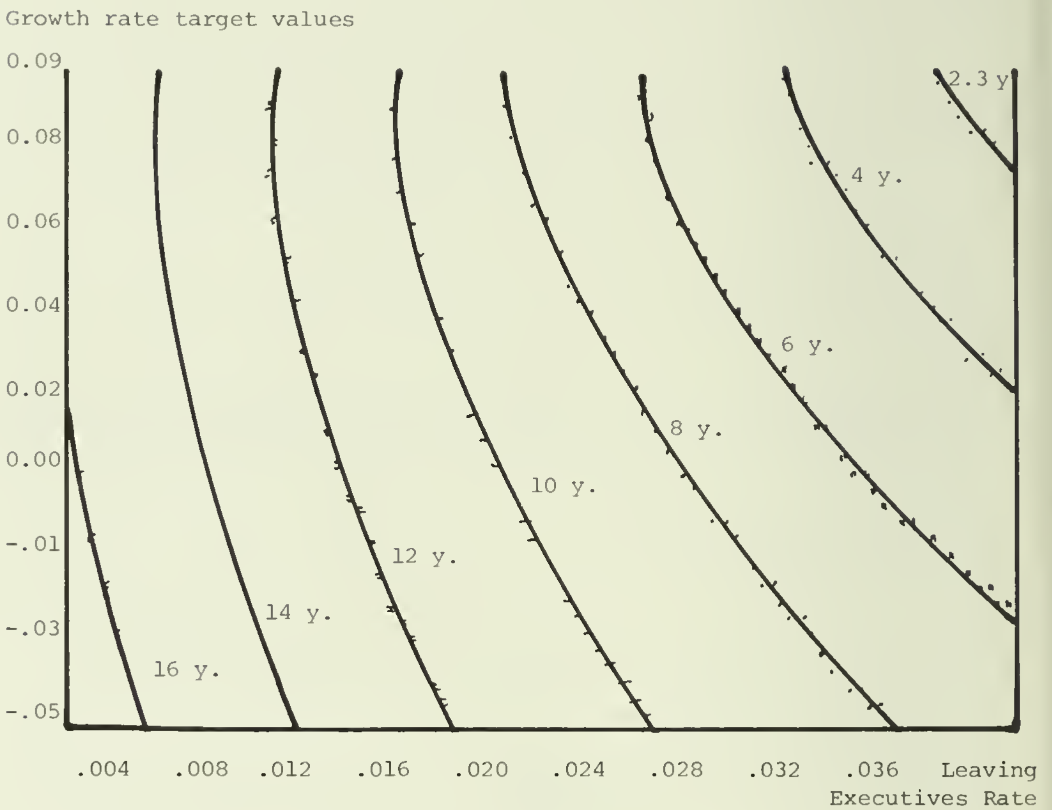
Response surfaces of the model showing important endogenous variables, such as success rates and mean waiting times as a function of extrapolation parameters were estimated using second order rotatable designs [47].

Figure 9.8 shows the plotted result of an experiment in which the mean waiting time in a grade was estimated as a function of the leaving rate in the same grade, a target value growth rate for other grades and different retirement and leaving rates.

PRODUCTION

The financial corporate models, especially the corporation model described earlier, are at present the planning models which are most intensively used at CIBA-GEIGY. From a methodological point of view the most ambitious model was, however, constructed for one of the operating divisions to describe the production, distribution and financial aspects connected with the sales of approximately 35 product groups to 65 sales countries. The product groups are fabricated in ten plants and production incorporated up

Figure 9.8. Results of rotatable design experiments with manpower planning model



to three different stages.

The model resembles the case study model described in chapter 8. Its hard core was initially a marketing submodel which generated and aggregated market forecasts for the product groups and sales countries. It was initially used for the divisions long range planning. When the long range production capacities of the production plants became subsequently available, attention was transferred more to a world-wide capacity analysis also taking the distribution of the product groups into consideration. More recently cost and other financial data have been collected in order to show the effects of the marketing and production areas on a financial model segment. Due to difficulties encountered in the collection and preparation of the financial data, the model is not used at present.

OBJECTIVES OF THE MODEL

1. The model was intended to generate demand forecasts by quantity over a ten year time horizon on the product group and country level. The product groups were detailed according to the production processes involved rather than to the chemical or physical nature of the products. Not only market developments, but also changes in the product mix and in the production technology had to be considered in the forecasts. The life time of the individual products typically ranges between four and ten years and so does the time required for research and the development of a new product. Hence, forecasts had to be made for as yet non-existing products as well as technologies. The demand extrapolation model was mainly descriptive using intuitively formalized estimates and guesses.
2. Based upon the forecasts and given long range capacity figures for the production locations a world-wide capacity balancing had to be carried out. The model was supposed to show the time dependent differences between anticipated sales by quantity and the available capacities taking into account consequences of changing technologies and quantitative as well as qualitative changes in the demand forecasting assumptions.
3. Based on user supplied and subjectively estimated production-distribution preferences the model was supposed to generate satisficing or even optimizing production and sales allocations.
4. Using local sales and cost data the model was intended to evaluate a marginal income analysis by product group and production as well as sales country considering the implications of product transfers, changes in prices and costs, transfer of production sites, or changes in the distribution policy.

MODEL DATA

Mainly three types of data were contained in the database of the model: Those which were available from the firms information systems, those that were collected manually within the firm for the project and, last but not least, data which were subjectively estimated and supplied by the model user.

Most of the financial model data were taken from the firms information

systems. These data were obtained on a local or a consolidated basis. Examples were product selling and transfer prices, sales by value, elements of variable costs such as advertisement expenditures, distribution costs, production and labor costs, or elements of period costs such as depreciation costs. It should be noted that these data were classified according to single product, product group, production location, selling daughter company and country sold to. Hence, various levels of data aggregation had to be dealt with. In contrast to the corporate marketing models described in the previous section, tree structures of data were of great importance.

Mainly external information to allow demand forecasting and the capacity data had been collected manually. The production departments of the producing daughter companies were asked to estimate and supply long-range production capacities with respect to the product-groups and the equipment installed. These capacities were typically defined in quantity units (e.g. kilograms, litres) per year. Sometimes the capacities were defined for single product groups, in other instances they could only be described with respect to several product groups, last but not least, for several production locations capacities depended non-linearily on the production mix of two product groups. An example is illustrated in Figures 9.9 and 9.10.

Five product groups are processed in four plants, Figure 9.9 shows in which sequence the product groups are processed in essentially three production stages. In the first stage all five product groups compete for a fixed capacity. Product group 5 may then be distributed to the customers, whereas group 4 is processed further in a special purpose plant and the three remaining groups compete for a yearly fixed capacity of a multi-purpose plant in production stage 2. Production groups 2 and 3 are distributed only after they have been processed in a third production stage. Here the available capacity is a funtion of the processed quantities of the two product groups as is shown in Figure 9.10 in a piece-wise linear approximation.

The user of the model supplied subjectively estimated parameters and exogenous variables for the marketing segment of the model. For some of the optimization investigations already carried out, subjectively estimated production-distribution preferences were used.

Equations

All model equations were so far deterministic. Demand D_{ijt} for a

Figure 9.9. Flow of product groups through coupled production stages

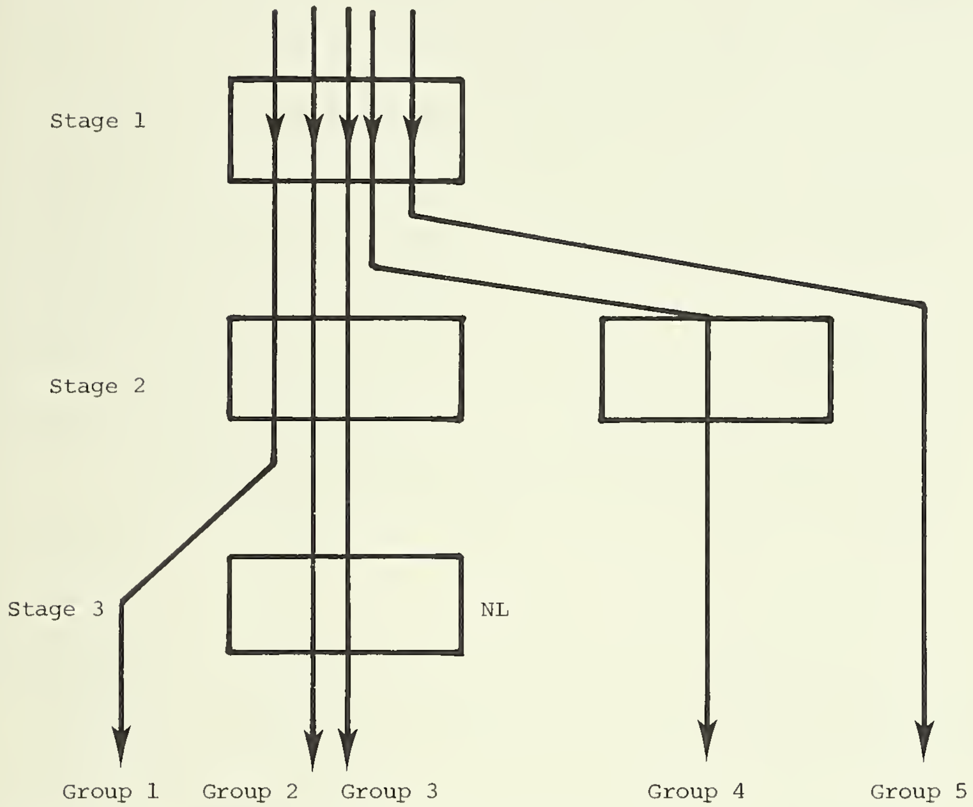
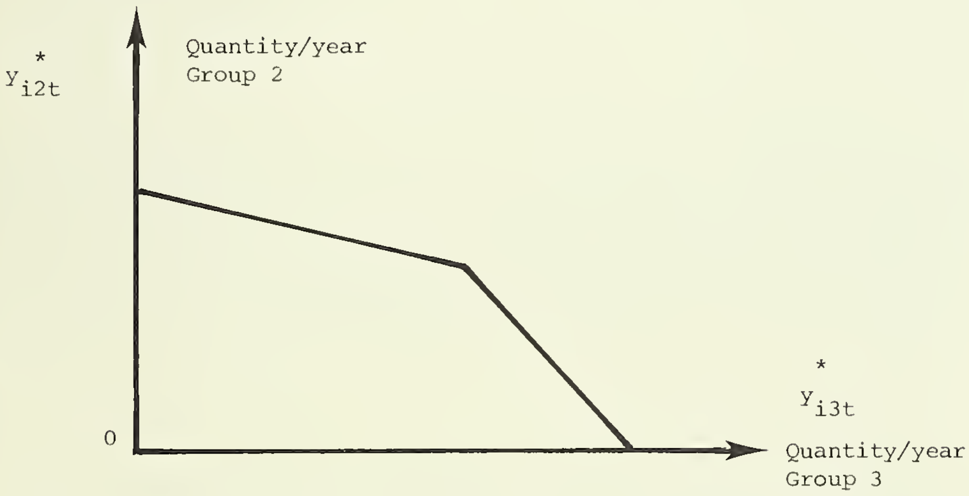


Figure 9.10. Example for non-linear capacity



product group i in a country j was extrapolated by simple formulae like

(9.10)

$$D_{ijt} = D_{ijo} \cdot (IE_{it} + IN_{it}) \cdot \frac{JN_i}{JE_i} \cdot IC_{jt} ,$$

where D_{ijo} is the demand for the last historical year, IE_{it} and IN_{it} are indices which describe the development of the volume proportions for existing (E) and new products (N) in a product group. The indices JN_i and JE_i describe the volume proportions of new or existing products in group i with respect to a world wide sales category. Finally IC_{jt} represents a country extrapolation index. All indices were specified by the user; the time dependent indices IE_{it}, IN_{it} and IC_{jt} were extrapolated or interpolated to target values using the practicioner models described in chapter 6.

Let y_{ijkt} denote shipments of product group i from plant k to country j, then eq. (9.10) defines demand restrictions of the form

(9.11)

$$\sum_k y_{ijkt} \leq D_{ijt}$$

for all product groups and sales countries. Some of the product groups are produced in single stage production processes. With given capacity figures C_{ikt}, capacity restrictions of the form

(9.12)

$$\sum_j y_{ijkt} \equiv y^*_{ikt} \leq C_{ikt}$$

were formulated for all plants; the user supplied subjective production-distribution preferences p_{ijk} and using the objective function

(9.13)

$$P_t = \sum_{i,j,k} p_{ijk} \cdot y_{ijkt} \Rightarrow \text{Max}$$

eq. (9.11) - (9.12) together with non-negativity constraints on all model variables describe a transportation problem. Slightly more complicated model relations were obtained for the multi-stage production processes shown in Figure 9.9 and 9.10. One obtains the restrictions

(9.14)

$$a_{11} y^*_{1kt} + a_{12} y^*_{2kt} + a_{13} y^*_{3kt} + a_{14} y^*_{4kt} + a_{15} y^*_{5kt} \leq C1_{kt}$$

for the first production stage

(9.15)

$$a_{21} y^*_{1kt} + a22\, y^*_{2kt} + a_{23} y^*_{3kt} \leq C21_{kt} \text{ and } a_{24} y^*_{4kt} \leq C22_{kt}$$

for the second production stage, where k = [1,10]. The parameters a_{ij} denote

quantity transformation factors, the coefficients $C1_{kt}$, $C21_{kt}$ and $C22_{kt}$ capacities of the first two production stages. The nonlinear production capacity in the third production stage may be described by the restrictions (9.16)

$$y^*_{2kt} + d_{1k} \cdot y^*_{3kt} \leq b_{1k}$$

$$y^*_{2kt} + d_{2k} \cdot y^*_{3kt} \leq b_{2k} \quad .$$

The parameters b_{1k} and b_{2k} denote the intercepts, d_{1i} and d_{2i} the slope of the restrictions shown in Figure 9.10. Relations (9.14) - (9.16) replace eq. (9.12) and together with eq. (9.11) and eq. (9.13) form a slightly more general linear program, which may be decomposed into a small linear program and a transportation program (viz. Wagner [58]). In both cases the model structure did not contain any interperiod restrictions as would e.g. arise if inventory processes were taken into consideration. A period by period optimization therefore delivered the global optimum.

Model Solution

Since the model's database did not contain enough historical data, no parameter estimation was carried out so far. The linear programs were solved with the Stepping Stone Algorithm and the Revised Simplex Method. The CIBA-GEIGY COMOS contains macro-statements to achieve this task.

Testing And Validation

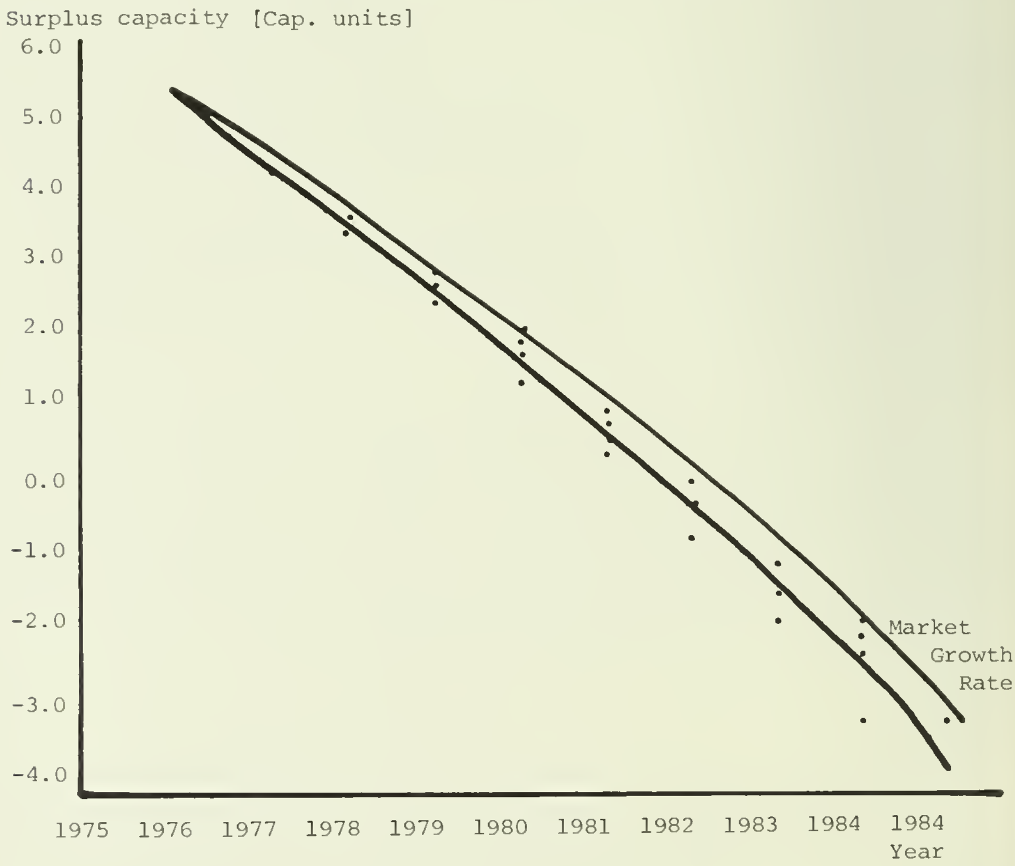
In order to test the numerical consistency of the demand forecasting models, some model runs were compared to alternatives that had previously been calculated manually with an effort of between three and four man weeks for each. Apart from this test of the consistency of model data and simple calculations in the marketing segment no validation other than what has been termed face validation has been carried out.

Implementation

The marketing segment of the model was used to generate long range demand forecasts in simple deterministic "What if?" type investigations. Parameters of the life cycle and the technology change forecasts functions were handled like decision variables and their effect on the demand was

also tested by the generation of deterministic response surfaces. Such results were then used as input for the capacity balancing segment or the production-distribution segment in order to show capacity bottlenecks or to optimize a solution with respect to user specified production-distribution preferences. Figure 9.11 shows an example of the information thus generated. Note that the points shown have not been calculated directly by experiments with the CSPM. This would have been too time consuming. Instead a quadratic "meta-model" of the CSPM was estimated using a random balance design and multiple regression. Fifteen experiments with the original model were used to estimate a world wide surplus capacity for a product group category as a function of time, a mean market growth rate for the selling countries, and an innovation rate for the product group.

Figure 9.11. Capacity utilization as a function of time and market growth. Experimintal design with production model



SOME CONCLUSIONS AND EXTENSIONS

There is an abundance of evidence to support the conclusion that corporate planning and simulation models may indeed be used in practice. Users, especially with budgeting and financial planning and simulation models [18, 21], have learned how to employ models as experimental tools and are often able to distinguish between questions a model may answer and questions which have to be answered outside a model. Model builders have on one hand learned how to build relevant models and on the other hand how to give answers to certain types of management questions. The development of CSPSs has certainly supported this development.

The known corporate modeling applications are very heterogeneous. This fact indicates that neither the environment a firm operates in, nor its organizational structure and planning process, nor the type of user a model is built for seem to decisively limit the corporate modeling approach as such. These factors certainly have a great influence on decisions concerning the type of model to be built and on the performance of the different steps of the modeling procedure in specific cases. But a successful implementation seems to be possible under a variety of conditions.

At this point one has to be prepared to answer some critique: a great proportion of the research work carried out in micro-economics, operations research, and econometrics deals with problems of model size, nonlinearity and chance which are also likely to arise if one describes a firm. Stating that CSPMs may indeed be successfully used in practice does not mean that the mentioned stumbling blocks of these disciplines have been overcome by corporate modeling. Indeed, one may say that corporate modeling has so far not tried to solve such methodological questions. Instead model builders and users concentrated their efforts more on tentative solutions to a number of interrelated integration problems employing also some available, robust, and easy to use management science methods.

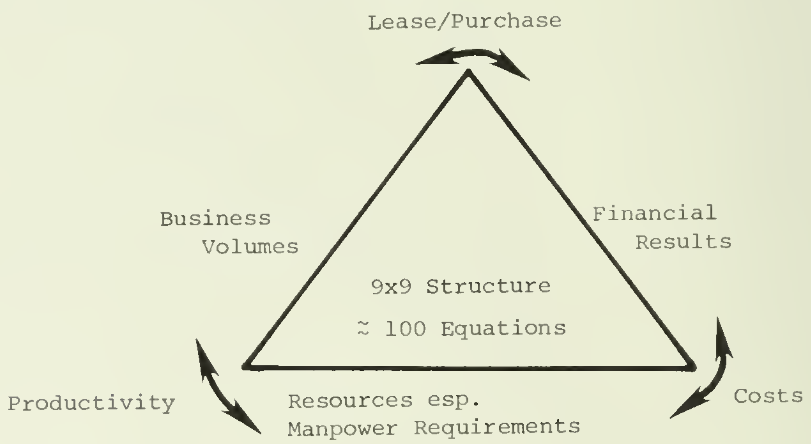
ORGANIZATION

Using either a central database or several decentralized databases, CSPMs frequently describe the activities of different organizational units of a company. According to the principles of model building previously described one will construct several submodels for a larger organization.

Their linkage is again likely to improve the internal and external consistency of planning and control information. The degree to which a company is decentralized and what type of planning procedure it possesses determines how, when, and by whom different submodels and their databases are used. Iterations between models may support the dialogue phase of a planning and control procedure.

An interesting approach to an organizational integration was due to IBM Corp. The company has developed a middle- to long-range target planning model at its headquarters [60, 52]. Figure 9.12 visualizes its main segments. It consisted of approximately a hundred equations which described IBM's business volume in NCV (Normalized Compute Values), linked to it a financial segment and a resources segment. For all segments target values were formulated for nine businesses and nine business regions. The model was solved by linear programming techniques.

Figure 9.12. IBM target planning model



Even more interesting than the structure of the model and solution method employed is its use: copies of the model and targets were sent to the subsidiaries who could use it as a frame for their own more detailed planning and for the planning dialogue.

Texas Instruments has developed world wide integrated and on-line planning databases and simple financial ratio models which both support a functional and organizational integration of planning activities [26]. Similar approaches will probably be seen more frequently in the future.

SUPPORT OF THE PLANNING AND CONTROLLING PROCEDURES

Many companies like CIBA-GEIGY nowadays possess formalized planning

and control procedures which on different levels of aggregation, time scale and content generate the information needed for the construction of CSPMs. Since CSPMs are formalized models, they largely exploit the numeric information thus generated, whereas the use of verbal and structural information for the formulation of model equations poses a great number of definitional and scaling problems. This is true for the normally more project oriented strategic planning process. This observation holds even more for the strategic management process which, in a verbal form, states general business objectives and restrictions to be obeyed for contacts with the socio-economic order a firm is embedded in or for relations among its employees. The question as to how far CSPMs may support the strategic management or the strategic planning process remains largely unanswered at present. Nevertheless, one should not forget that many strategic problems, as arise in connection with the planning of large investments, investment portfolio selection, merger and acquisition analysis may be described numerically. A series of simulation experiments at least supply information as to how far the position of the firm is endangered by incorrect decisions. Furthermore, such experiments may establish a consistency with the middle- and short-range planning process which does not disguise structural uncertainty by the often artifical accuracy of the latter. Special attention should be given to the integration of mental and verbal as well as formal planning models, notably for the strategic planning process. Figure 9.13 supplies a self explanatory example how this has been achieved by SUCHARD Company (viz. Beguin, Probst [4])$_2$. The computer based activities are performed in interactive mode. Such a combination has another quality than a mere automation of a predefined manual process.

TYPES OF MODELS

The corporate modeling case studies described in previous chapters constitute a family of models which may either be independently used or integrated on user request. For a large multidivisional and multinational firm this result is not a surprise. In fact, the information available at the headquarters allows only a limited representation of and experiments with e. g. specific subsidiary and market models. More specific models must be developed and operated in a decentralized fashion. The trend towards third generation planning systems and decentralized computing will quite likely increase this tendency (viz. also Szyperski et al. [55]).

Figure 9.13. A corporate planning system.

The risk connected with these developments is that a company may easily end up using various and not compatible CSPSs and models. While relatively few arguments speak against a decentralized model development, economic and consistency reasons call for a coordinated development. The choice of a common CSPS as planning laboratory and decision support system may possibly constitute a unifying framework. Planning information systems with extended analytical capabilities may fulfil the requirements for a decentralized model development.

FUTURE DEVELOPMENTS

Model builders and users often seem to know which type of planning activity may be supported by a corporate model and where the limitations of its application are. However, one may expect that the boundary between problems which are solved within the scope of a CSPM and outside of it will not remain the same in the future.

Several developments may be expected in this respect and similar to the last decade they will probably be a consequence of the changes and developments in data processing and planning philosophy as well as technology.

NEW TYPES OF APPLICATIONS

It has been noted before that the structure of corporate models is expressed in equations. Although they may change in time or with respect to certain conditions, i.e. contain non-conjunctive terms, they require a user specification which - due to structural uncertainty in the phenomenon described - he is frequently not able to supply.

EXTERNAL DATABASES

Especially in the marketing area it is often not altogether clear which variables should be used in an equation and whether they should stay in there for all time. If historical measurements of the model variables are available, these problems may to some extent be solved by econometric specification testing or the introduction of dummy variables to take special influences, e.g. changes of oil prices, into consideration. For this type of application it is important for business firms to obtain accurate

and timely information as well as forecasts of macroeconomic, industry and competitor variables. Such inputs may be purchased from specialized private companies, international and state organizations, or own data collection and modeling. Modeling activities with such an environmental database fit very well into the framework of CSPMs known so far. It only remains to be determined how far a company should become involved in macroeconomic modeling. The survey by Naylor and Schauland [42] indicates that a large percentage of the firms engaged in corporate modeling have access to external databases and models already (viz. also [10,22,37,52]). Although not many of them may couple these models directly to their corporate planning models yet, one should expect that the future will see such a combined use - and be it across a mental interface - more frequently.

STRUCTURAL MODELING

If no historical data are available, one has to cope differently with structural uncertainty. One possibility is to exclude it from the models altogether and to organize a verbal or semi-quantitative planning process around the model (Ansoff [2]). One might for example ask planning units of a firm to first verbally describe threats to and opportunities for the business, then to formulate these threats and opportunities coming from the environment of the firm which can be used as data input to a CSPM. One may then employ such an enlarged planning database for simulations after the user has subjectively defined a strategy mix and appropriate tracking signals to call in certain strategies. Also fast heuristic methods or further developed mathematical programming algorithms may support an appropriate strategy selection and the "What if?" experimentation described above.

There are several possibilities to also, at least partially, incorporate a more formal approach to structural modeling into the modeling process itself.

One is to support the model specification step by the graphical analysis described in chapter 5 or other techniques such as Industrial Dynamics representations. Like network techniques in scheduling applications these graphical representations of a model structure may help in the conceptualization of possible structural alternatives and may partially be evaluated on a computer.

Another example is the combination of formal planning methods together

with data classification methods described in chapter 3. If external and competitive databases will be available more frequently, the demand for methods which search and group external data and represent them in various combinations will increase. Models as underly Zipf's law or the experience and learning curves together with classification and pattern recognition methods will be used more often to exploit structural a priori knowledge of the model users.

DATA PROCESSING

The development of planning procedures has strongly been influenced by the progresses made in computer hardware and software development. Third generation planning procedures which are presently discussed and implemented call for the interaction, participation and negotiation between organizational levels and functional areas of a firm (viz. [2,55]). Unlike with fixed structure and content first and second generation procedures an important part of the planning process incorporates a varying number of participants, a changing planning content, and irregular ad hoc performance. The support of such procedures must be achieved by further developed CSPSs.

Improved telecommunication and interactive computing are some prerequisites for a third generation planning procedure of a firm with regionally distributed organizational units. A flexible and up to date planning database allowing at the same time for decentralized modeling and a company-wide integration may be achieved using intelligent terminals and front-end computers in a computer network. The CSPSs which allow for distributed planning and modeling.

In order to avoid the distortion of planning information newer procedures tend to involve more planners with a different educational background and experience. CSPSs must support both planning and data processing experts and non-experts in a fashion which avoids user frustration either due to too slow and unspecific dialogues or too high technical requirements. CSPSs should allow the construction of customized dialogues and further implementation research is necessary on suitable questionnaire designs. Databases and model as well as method libraries of CSPSs must be adapted to this usage.

Especially in the area of strategic planning future CSPSs should allow for a better integration of formal and purely mental models for badly structured planning problems. To exploit the user's ability for pattern

recognition and association set statements and the means for a graphical representation of model data have to be further developed. One may well imagine that graphical input, e.g. on light screens, may substitute the statement oriented specification of practicioner methods for a subjective data extrapolation and interpolation used at present. Graphs and networks to represent a model structure may be input to a CSPS which then translates it into a formal equation model. Similarily one may imagine the CSPS supported evaluation of textual user input e.g. regarding preferences or risk level for a particular solution.

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FOOTNOTES TO CHAPTER 9

1. The original article [50] contained an error for the 1975 measurements.

2. By permission of the authors.